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An Empirical Study of Serial Correlation in Stock Returns

Cause-effect relationship for excess returns from momentum trading in the Norwegian market

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NORGES HANDELSHØYSKOLE

Abstract

This paper documents the maximum *theoretical* excess return on the market to 3.8% monthly from momentum trading in Norway and estimates the *economical* excess return to be marginally higher than 1% per month when accounting for microstructure influences. We find that the excess returns of various momentum strategies are not explained by systematic risk or exposure to other factors such as size or book-to-market value. We uncover a positive correlation between types of investor and the degree of momentum in the market. Studying business cycles has provided evidence of reversals following bust periods which are in-line with behavioral theories of overreaction.

Preface

After investigating numerous possible hypotheses for this paper we have decided to expand our knowledge of empirical finance. At NHH, few classes are taught in empirical finance; we consider this master thesis to be a great opportunity to reach a respectable level of knowledge and understanding within the field. Inspired by an article in the Economist on a recent London Business School research project on momentum in stocks markets globally, we dug deeper to uncover previous findings on the topic. That was the starting point for this paper; we hope that the reader will be as inspired by our research and findings as we are from the work of our predecessors.

We wish to thank Assistant Professor Per Östberg for valuable guidance and for keeping us on the right track when digressions has threatened to steal our attention from the main core of the topic. We would also like to thank Professor Thore Johnsen of NHH and Børsprosjektet for providing us with the data for our studies.

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1. Introduction

Can historic observations of a publically traded company's performance be used to predict their future performance? That question is the essence of this paper and there are several ways of answering it; for example one could look at various performance measures such as earnings or stock prices. We have chosen to work with the latter, or more specifically, we are examining whether there is a tendency for stock returns to trend in the same direction and thereby establish whether there is momentum in the stock market. We test whether or not it is possible to earn abnormal returns on the Oslo Stock Exchange by forming winner and loser portfolios on the basis of past stock returns.

Empirical evidence from vast research in several markets document this anomaly known as momentum. A recent London Business School research with 108 years of data covering about 85% of the world equity market capitalization concluded that "The momentum effect, both in the UK and globally, has been pervasive and persistent" (Dimson, Marsh and Staunton, 2008). Rouwenhorst (1998) finds in a study of 12 European countries including Norway in the period from 1978 to 1996 that an internationally diversified momentum portfolio earns about 1% excess return on the market per month.

Much of the research on momentum has been dedicated to trying to explain the excess return earned from following such a strategy by adjusting for various factors such as the size effect, book-to-market ratios and market risk. During the last 25 years, attempting to explain investor behavior has also gained a lot of attention in trying to explain the momentum effect. Jegadeesh and Titman (1993) find that excess returns from following momentum strategies are not due to systematic risk or to delayed stock price reactions to common factors such as the January effect. Jegadeesh and Titman (2001) also present evidence which supports the prediction of behavioral finance models that suggest that the momentum effect is due to overreactions in the market. Grinblatt and Keloharju (2000) analyze different investor groups and find that the degree of momentum behavior seems to be strongly correlated to the degree of sophistication of the investor types.

Kloster-Jensen (2005) finds that a momentum strategy on the Oslo Stock Exchange (OSE) yields significant positive returns, but this is due to a large extent by compensation for taking on added systematic risk. Hence, he concluded that there is no momentum effect in the

Norwegian market. Conversely, Myklebust (2007) examines sixteen different time-strategies for momentum trading on the Oslo Stock Exchange and finds that all strategies yielded positive excess returns, which could not be explained by market risk or the size effect.

Up until now OSE momentum research has been limited to using data samples of stocks that have been traded during the whole sample periods. This has narrowed the data sets to about 70 stocks which can be compared to the actual number of almost 600 stocks that have been listed during the last eleven years, which is the time period we examine. Our approach is different; and by analyzing a dataset of 598 stocks we can provide evidence of the maximum *theoretical* excess return that can be earned from a momentum strategy on the OSE. This is accomplished by 16 different time-strategies that are comprised of a forming period (ranking period of the stocks) and a holding period. These strategies are evaluated by accounting for risk exposure, or more precisely systematic risk (CAPM) and the size effect using a two-factor regression model.

The total dataset is then screened based on a set of rules that provides us with 123 stocks suitable for evaluating the maximum *economic* excess return that can be earned (i.e. a dataset that gives us the opportunity to test the momentum strategy when accounting for microstructure influences such as transaction costs). In this part of the study we explore one time-strategy, which we call “the best strategy portfolio”.

As with many of our predecessors, we attempt to explain excess return by accounting for various factors; here we expand the model to include a third factor: book-to market ratio, using the Fama and French three factor model.

We also probe areas that have not been explored in earlier momentum research for the Norwegian stock market. We test for seasonality by deducting and secluding January returns. Through descriptive studies of the dataset we highlight any under or over-representation among sectors in the momentum portfolios and provide intuitive explanations to why some sectors are biased towards either the loser portfolio or the winner portfolio. Moreover, we examine the momentum returns throughout business cycles to identify any variations in good times and bad times.

Finally, we expand the discussion of momentum explanations by building on Grinblatt and Keloharju’s 2000 research on the behavior of different investor types. We find that there has been a development over time in the type of investors that are active on the Oslo Stock Exchange and we examine whether this could be correlated to an increase (or a decrease) in the momentum effect over time.

2. Background information

Anomalies such as the momentum effect and mean reversal are empirical results that do not appear to be consistent with traditional theories of asset-pricing behavior. According to Fama (1991), these anomalies indicate either market inefficiency (opportunities to earn abnormal return) or inadequacies in the underlying asset-pricing model. In other words, in order to determine whether markets are efficient or not, we need an accurate model of market equilibrium, this is referred to as the Joint Hypothesis problem which we will discuss in chapter 3. Assuming a perfect model of market equilibrium, the question is whether or not markets are efficient; if markets are not efficient in the weak form, which according to Fama (1970) means that "stock prices already reflect all information in historic price- and turnoverdata" it is possible to earn abnormal returns from picking stocks based on historical returns. In chapter four of this thesis we will look at previous research of strategies that try to exploit this market failure such as momentum and mean reversal strategies. We also investigate various explanations besides the underlying model of market equilibrium for the momentum effect which imply that markets are not truly inefficient even though we find evidence of the momentum effect. For example, whether or not the excess returns of momentum strategies are due to inefficient markets or just a compensation for added risk.

2.1 Momentum and Mean reversals, weak-form tests

Many previous tests of efficient markets, including Jegadeesh and Titman (1993), on we base much of our work, were tests of the weak form. These tests were attempting to ascertain whether investors could earn abnormal returns by studying past returns given an accurate model of market equilibrium.

2.1.1 Short horizons (momentum)

One of the most recognized market imperfections in stock returns is momentum. This refers to a continuing tendency of stock prices to move in one direction. When testing for the momentum effect, one is actually measuring the serial correlation of stock market return. In other words, we test whether today's return is related to past returns. Jegadeesh and Titman (1993) found in a study of stock price behaviour a momentum effect in which stocks that performed well during the last three to twelve months continued to do so for the following three to twelve months. Conversely the recent performance of the worst achieving stocks for the same horizons also continued over time. They concluded that while the performance of individual stocks is highly unpredictable, portfolios with the 10-15% best performing stocks in the recent past appears to outperform other portfolios.

2.1.2 Long horizons (mean reversion)

We have two types of serial correlation: positive and negative. Positive implies that past positive returns are followed by future positive returns and momentum in the market occurs. Negative serial correlation means that past positive returns are followed by future negative returns which are referred to as reversal. As above mentioned, studies of Jegadeesh and Titman (1993) and also Fama and French (1988) among others, have found evidence of momentum returns in stock market prices in short horizons. Whereas on longer horizons, they have found evidence of reversal. DeBondt and Thaler (1985) also found evidence of negative serial correlation in the performance of the market on longer horizons of three to five years.

3. Explanations for the momentum effect

Previous studies have found evidence for a momentum effect on short horizons, from one to twelve months, and for mean reversion on longer time horizons. Does this mean that markets are really inefficient or is there another explanation for the momentum effect? The sources of the momentum effect are hotly debated, yet scholars have thus far not come to an agreement. In this chapter of the thesis, we will touch on a few explanations which will later be applied to our own method. Some mean that these results prove that markets are not efficient in the weak form since the presence of momentum indicates that stock prices are predictable. While certain researchers believe that markets are efficient and that the momentum effect is just due to inadequacies in the underlying asset-pricing model, a product of data mining or a compensation for risk. Others argue that transaction costs explain momentum or that anomalies such as the January effect may participate in explaining momentum. Off course then we still need to explain these anomalies in order to judge whether markets are efficient or not.

Scholars who believe that markets are truly inefficient are leaning more towards the concept of behavioral finance (which for the last 25 years has become more and more prominent) as an explanation for the momentum effect. Hong and Stein (1997) for example, present behavioural models that are based on the idea that momentum profits arise due to biases that affect the way people interpret information. This implies that there is no rational explanation for the momentum effect and that markets are inefficient.

3.1 Sources of momentum profits

Jegadeesh and Titman (1993) analyze the sources to why a momentum strategy yields excess return. They decompose the momentum profits into two components relating to systematic risk and a third component relating to idiosyncratic risk. It is important to determine whether the sources of excess return is related to the first two systematic risk components or the third component relating to idiosyncratic risk to determine whether markets are efficient or not. If the profit from following a momentum strategy is due to the first two components, the profits do not necessarily imply that markets are inefficient since it may only be a compensation for taking on risk. On the other hand, if the excess returns are due to the third idiosyncratic component, then the excess return would imply market inefficiency.

The following representation of momentum strategies is derived from Jegadeesh and Titman's (1993) work "Returns to buying winners and selling losers" based on that in Jegadeesh (1987) and Lo and MacKinlay (1990).

A stocks return is described as

$$\boldsymbol{r_{it} = \mu_i + b_i f_t + e_{it}}$$

Where r_{it} is the return on stock *i* at time *t* and μ_i is the unconditional expected return on stock *i*. The second term b_i is the factor sensitivity of stock *i* which is multiplied with f_t the unexpected return on the factor portfolio, while the last term e_{it} is the firm specific component of return.

The excess return of a momentum strategy implies that stocks that have done well in the past continue to perform well in the subsequent periods. This implies that:

$$\boldsymbol{E(r_{it} - \bar{r}_t | r_{it-1} - \bar{r}_{t-1}} > 0) > 0$$

And

$$\boldsymbol{E(r_{it} - \bar{r}_t | r_{it-1} - \bar{r}_{t-1}} < 0) < 0$$

Where $\bar{r}_t$ is the cross sectional average return. So, we have a momentum effect if the return of stock *i* minus the markets average return is positive given that past returns of the stock *i* is bigger than the past market average return. Or vice versa if the return of a stock *i* minus the markets average return is negative given that past returns of the stock *i* is smaller than the past market average return,

$$\boldsymbol{E\{(r_{it} - \bar{r}_t)(r_{it-1} - \bar{r}_{t-1})\}} > 0$$

The equation above shows the profit for a momentum strategy; where one buy stocks that in the past have performed better than average, and sells stocks that have performed below average.

The equation above can be decomposed into three different terms given the one factor model described above:

$$\boldsymbol{E\{(r_{it} - \bar{r}_t)(r_{it-1} - \bar{r}_{t-1})\} = \sigma_\mu^2 + \sigma_b^2 Cov(f_t, f_{t-1}) + \overline{Cov}_i(e_{it}, e_{it-1})}$$

Where σ_μ^2 and σ_b^2 is the variance of expected returns and factor sensitivities respectively. The first term denotes the variance in expected returns; if the differences in expected returns between stocks are high the returns of momentum strategies will be higher. This is because a momentum strategy will tend to pick stocks with a large expected return. Hence, the larger the first term, the larger the expected return from following a relative strength strategy.

The second part of the equation is related to the potential to time the factor. If the factor portfolio returns experience positive serial correlation, our strategy will pick stocks with high betas. While the last term is the average serial covariance of the idiosyncratic components of security returns, in other words the firm specific risk.

To determine whether or not the excess returns of momentum strategies are due to inefficient markets or just a compensation for risk, it is important to determine the sources of profits. If our excess returns are due to one of the first two terms, we cannot conclude that markets are inefficient; the excess returns may just be attributed to bearing systematic risk. If on the other hand excess returns are due to the last term, then the excess return can imply market inefficiency, given the traditional theories that stipulate that unsystematic risk can be diversified away and therefore does not add to the expected return. If this term is negative, it will imply that stock prices overreact to firm-specific information and correct the overreaction in the following period hence it will contribute to mean reversal profits. If the last term is positive, it will imply that stock prices underreact to firm-specific information which will increase momentum profits. This is in line with our behavioral finance theory below.

3.2 Behavioural finance

Since the 1980s, the academic dominance of efficient markets has become far less common. Economists began to believe that stock prices are at least to some extent possible to predict. A new kind of economist emphasizes behavioral elements of stock-price determination, and has come to believe that future stock prices are somewhat predictable on the basis of past stock price patterns (Malkiel 2003).

Hens and Bachmann (2007) argue that investors overreact to new information as a consequence of the availability bias which is a tendency of individuals to judge the relevance of information based on how easy it is to recall. This situation where individuals tend to react more than correct take place for example when the price of a firm's stock inflates in response to good news and later the price corrects in the opposite direction without any additional information. If individuals overreact to news due to the availability bias, past winners may become overpriced and past losers may become underpriced. This is a signal that investors react too strong towards recent news - good or bad - reflected in the recent stock prices. Later, investors may realize that their reaction was too strong and hence the stock returns start to rebound. Overreaction to news explains momentum in the short run and mean reversal in the long run.

DeBondt and Thaler find empirical evidence for this effect, in their article "Does the stock market overreact?" (1985), they ranked stocks listed on the New York stock exchange based on their return over a period of three years. Based on these rankings, they have created a "winner" and a "loser" portfolio with 35 stocks in each. They tracked the performance of the respective portfolios against a market index for three years and found that the loser portfolio systematically overperforms and the winner portfolio systematically underperforms.

Another well known bias is the representativeness bias which according to Hens and Bachmann (2007) is the tendency of individuals to:

1. Estimate probabilities in dependence of their pre-existing beliefs even if the conclusions are statistically invalid.
2. Believe that small samples represent entire populations.

This bias leads investors to believe that the process of returns has changed in favor for the better after a relatively short sequence of good returns; since one believes that the sample return is equal to the true population return when applying the representativeness bias. This bias of the investors triggers prices to become too high or too low, which may generate momentum in the short run and reversals in the long run: one could say that there is an overreaction in the market. After some time investors realize that there was an overreaction and stock market returns reverse. Hence, it is possible to earn abnormal returns on longer horizons by buying the losers and selling the winners: a so called mean reversal strategy with a ranking period of at least 12 months.

Empirical foundations for overreaction causing abnormal returns from following momentum strategies are weaker than empirical evidence for underreaction to cause momentum.

As mentioned previously, another reason for momentum strategies to earn abnormal returns is underreaction. Underreaction can, according to Hens and Bachmann (2007), be explained by *Anchoring and Conservatism*. Anchoring is a phenomenon that occurs when people tend to be overly influenced in their assessment of some amount by random amounts mentioned in the statement of the problem. The anchoring heuristic may lead to underreaction if people use the initial or current value and underweight new information. Conservatism can be seen as a consequence of anchoring upon an initial probability estimate. High costs of processing new information can be an explanation of conservatism. Information that is either presented in a statistical form or abstract in nature may cause investors to revise their beliefs insufficiently in accordance with new information. Momentum should therefore be stronger when news influencing the stock's value is difficult to analyze. There is empirical evidence supporting this belief. Momentum is stronger in stocks that are hard to value, such as young firms and small firms stocks that are not frequently analyzed. Momentum will also be stronger when news is presented over a longer period than when news arrives at the same time and the consequences are apparent. If individuals behave this way, prices will probably adjust slowly to information, and once the information is fully included in prices, there is no further predictability in stock returns. This explanation suggests that the returns in the periods after the holding period will be nothing.

If initial values, called "anchors", influence the investors' expectations then stock prices will need some time to fully reflect this new information. Hence stocks with positive surprises will earn abnormally high returns while stocks with negative surprises will earn abnormally low returns in the months following an announcement. Such information, for example earnings releases can produce a phenomenon called Post- Earnings- announcement Drift (PEAD). According to Bernard and Thomas (1989 and 1990) stocks with positive earnings surprises earn abnormally high return in the months after the announcement and stocks with negative earnings surprises earn abnormally low return in the following months after the announcement. Empirical evidence of this is found by Bernard and Thomas (1990) when they study about 85000 quarterly earnings announcements over the period from 1974 to 1986. Each calendar quarter they rank stocks based on the unexpected earnings report and build ten portfolios. Over the following 60 trading days, a long position in the top portfolio (with firms reporting positive earnings surprises) and a short position in the bottom one (with firms reporting negative earnings surprises) yields an abnormal return of 4.2% or about 18% on an annualized basis. After extending the holding period to 180 days, the difference between the return of the top and the bottom portfolio becomes 7.75%.

Typically, the PEAD lasts one year, after that there are no earnings surprises, hence the earnings fall below the analysts' expectations, which is a signal that the underreaction effect is over and it is time to sell the stock.

To explain underreaction and overreaction, Hong and Stein (1997) model a market populated by two groups of rational agents. They name the two respective groups "news watchers" and "momentum traders". The news watchers' create their strategies based on private information, but do not extract other news watchers information from prices. The information the news watchers have is only partially reflected in the price when news is announced and prices underreact in the short run. The underreaction means that "the momentum traders" can earn momentum profits by trend chasing. This part of the model explains underreaction that leads to momentum profit, while overreaction is explained by the "momentum traders", attempts to profit on trends which inevitably must lead to overreaction at long horizons.

Summed, up the underreaction explanation suggests that the returns in the periods after the holding period will be nothing, while overreaction suggests that returns in the period after the holding period will reverse. We will use this insight to attempt to determine the reason for the momentum effect later in our paper.

3.3 The Joint-hypothesis problem

Fama demonstrated that the notion of market efficiency could not be rejected without an accompanying rejection of the model of market equilibrium. This concept, known as the "Joint-Hypothesis problem" has continually vexed researchers.

Although ambiguity about information and transaction costs makes it more difficult to determine whether a market is efficient or not, the Joint-Hypothesis problem creates an even bigger problem when one is trying to determine whether a market is efficient. Fama (1991) argues that market efficiency is not testable unless one has an accurate equilibrium model. In other words, market efficiency must be tested jointly with a model of equilibrium: an asset pricing model. The point here is that if there is evidence of anomalous behaviour in returns, (which makes the market appear inefficient), this should actually be split between market inefficiency and a bad model of market equilibrium. The Joint-Hypothesis stipulates that one can never reject efficient markets.

Tests of market efficiency therefore imply that we have as a foundation for our research a accurate model of market equilibrium. Common models are the CAPM (the Capital Asset Pricing Model) and Fama and French's Three Factor Model, in this paper we use both models. The CAPM has a few shortcomings; first, it assumes that asset returns are normally distributed random variables, also it assumes that variance is an adequate measurement of risk. The CAPM does not take into account the effect of behavioural finance. Since it is frequently observed that markets are not normally distributed, this model does not seem to be as accurate as it was once considered 40 years ago. Fama and French (1992) developed a three factor model which is more complicated than the CAPM; risk is determined by the sensitivity of a stock to the overall market, to a portfolio that reflects the relative returns of small versus large firms and a portfolio that reflects the relative returns of firms with high versus low ratios of book-to-market value. This model does not seem to oversimplify the market as the CAPM does, and is therefore more successful in describing market behaviour. Fama and French try in 1993 to explain momentum and long time mean reversion by utilizing this three factor model; they find that it explains mean reversion, but not the momentum effect.

3.4 Data Mining

Others argue that the momentum effect is a product of data mining. Jegadeesh and Titman (2001) argue that since stock data and computer resources are easily available and there may be a possibility to earn large payoffs if one is capable of creating a good predicting stock model, both in terms of publication fees and money management: a wide variety of strategies may have been tested by different individuals. It therefore may be hard to decide the significance of each test. This can, according to Jegadeesh and Titman, be a reason to conduct similar empirical tests over a wide variety of time periods and for different markets, so that the significance of empirical findings is not just due to coincidences.

3.5 Conrad and Kaul hypothesis (Risk)

Some argue that for momentum to exist, there must be inherent biases in human behavior as mentioned above, while others argue that the abnormal profit from momentum strategies is only a premium paid for taking on excess risk. Conrad and Kaul (1998) for example, argue that profitability of momentum strategies could only be due to cross sectional variations in expected returns and not to any predictable time series variations in stock returns. They start with the hypothesis that stock prices follow random walks with drifts and that these drifts vary across stocks. Further they suggest that the differences in drifts across stocks explain the momentum effect. This is because this drift can be looked at as the expected return of the various stocks. In other words, they suggest that the higher returns of winners in the holding period represent their expected rates of return and therefore predict that the returns from following a momentum strategy will be positive in any subsequent time period. If the Conrad and Kaul hypothesis hold, stock prices will not reverse over longer horizons. Lo and MacKinlay (1990) note that stocks with high expected returns in contiguous time periods are expected to have high realized returns in both periods and vice versa. When buying a stock with a high expected return and selling a stock with a low expected return (as one does while following a momentum strategy), one will then earn a profit from following this strategy as long as there exist differences in expected returns in the market; stocks with high expected return have a higher risk than stocks with a lower expected return.

Conrad and Kaul (1998) conclude from analyzing several momentum strategies that these strategies only pick stocks with high expected returns and hence a high required rate of return. They further suggest that the reason for this strategy being profitable is that one buys stocks with high risks and sell stocks with low risks. Conrad and Kaul's prediction is that the profits from the momentum strategy should be equally positive in any subsequent period due to exposure to risk, as opposed to our behavioral models which predict that overreaction will lead to long time reversal or returns equal to nothing in the period after the holding period.

3.6 Other factors

3.6.1 The Size effect

Jegadeesh and Titman (2001) finds that there is greater momentum for smaller than larger firms. Small companies have a tendency to yield higher returns than big companies on a short horizon (< 1 year). This is related to risk, and is possibly just a compensation for added risk associated with smaller firms. Reasons include that smaller stocks may be less liquid than bigger stocks and hence investors demand an extra return as a compensation for bad liquidity. Small firms may also have less secure earnings and therefore have a larger probability of bankruptcy in bad times. This effect was originally discovered by Banz in 1981, who examined the historical performance of stocks on the New York Stock Exchange by dividing these stocks into ten portfolios each year according to firm size. He then finds that even when returns are adjusted for risk, the small firm portfolio outperforms the large firm portfolio by an average of 4.3% annually.

From the early nineties to present day the momentum strategy has become more popular among institutional investors due to the empirical evidence supporting it. One might expect that this has diminished the difference in momentum between small and large stocks. This is because the trading activities of these institutions will add to the momentum effect in a larger extent for bigger stocks than for smaller stocks since momentum strategies demand frequent rebalancing and larger stocks can be traded at lower costs than smaller stocks.

3.6.2 The B/M ratio

Daniel and Titman (1999) find that momentum profit is higher when the strategy is implemented on growth stocks, stocks with a low book-to-market value as opposed to value stocks (high book-to-market value). This may be explained by introducing the overconfidence bias. This bias is according to Hens and Bachmann (2001) "a tendency of individuals to express confidence in their judgments that exceeds the accuracy of those judgments". Overconfident investors overestimate their stock-picking abilities, they overestimate the probability that their personal assessment on the value of a particular firm is more accurate than the assessment of other investors. This effect is more prominent the more ambiguous the task at hand may be, hence the overconfidence bias hypothesis suggests that momentum is likely to be greater for growth stocks than value stocks since it according to Jegadeesh and Titman (1997) is harder to evaluate growth stocks than value stocks. Lakonish, Shleifer and Vishny (1994) on the other hand find that a strategy which buys value stocks, stocks with a high book-to-market value, were profitable on a horizon of three to five years on the NYSE in the period 1963 to 1990. They found that the mean reversal strategy on a longer horizon is affected by the book-to-market ratio as the momentum strategy is on shorter horizons.

3.6.3 Seasonality

Jegadeesh and Titman (2001) find an apparent Seasonality/January effect in momentum, they find that the winner portfolios do better than the loser portfolios in all months but January, where the loser portfolios do significantly better than the winner portfolios.

Some argue that this effect is to be tied to tax – loss selling at the end of the year. People sell off stocks which have made losses the previous months to realize their capital losses before the end of the tax year; these investors probably do not put their income from these sales into the market until January. Then this excess demand in January will create an extra demand for stocks which will cause an upward pressure on prices known as the Seasonality effect.

Marquering (2006) shows that the Seasonality effect as an anomaly has disappeared with time, several other anomalies have also disappeared as they have become publically known or been explained by Fama and French's Three Factor Model. The momentum effect on the other hand is an anomaly which has yet to be explained.

3.7 Microstructure influences

Even though we find evidence of the momentum effect, it does not necessarily imply that markets are inefficient due to the reasons mentioned above. There are other factors present that might eliminate any excess return from following a momentum trading strategy when accounted for. Therefore under a pragmatic and modern definition of market efficiency such as Jensen's (1978) definition, a market that does not exhibit momentum when adjusting for microstructure influences will not be classified as inefficient.

A market is efficient with respect to information set θ_t if it is impossible to make economic profits by trading on the basis of information set θ_t." Jensen (1978)

3.7.1 Transaction costs

One factor that should be accounted for is transaction costs, after adjusting for such costs the excess return from following a momentum strategy may be eliminated.

It is one thing to earn abnormal returns from following a momentum strategy without considering transaction costs, but in practice the return of an investment strategy can only be measured after taking transaction costs into consideration. By transaction costs we mean such costs as bid-ask spreads, taxes and brokerage fees. These costs vary considerably and are different from investor to investor; therefore it is quite common not to consider transaction costs. Jegadeesh and Titman (1993) for example do not consider transaction costs and find that it is profitable to follow a momentum strategy, then when Lesmond, Schill and Zhou (2001) review their work they find that the returns from following a momentum strategy is no longer statistically significant after considering transaction costs.

A momentum strategy has short holding periods often less than 12 months, and is therefore rebalanced frequently. This will obviously incur large transaction costs. According to previous empirical studies, the momentum effect is more prominent in portfolios consisting of small stocks, which further increase transaction costs. This is due to the fact that smaller stocks are less liquid, and may have a considerable bid-ask spreads. Lesmond, Schill and Zhou (2001) report that differences in the momentum effect across stocks may be due to differences in transaction costs and sometimes totally eroded by the transaction costs of following a momentum strategy.

According to previous studies such as Hong, Lim and Stein (2000) and Jegadeesh and Titman (2001), most of the momentum effect is generated by the loser portfolios. To exploit this, it is necessary to short sell these loosing stocks, which often incur high transaction costs and is not necessarily possible to realize. This is because the market for shorting stocks is different from buying stocks since one has to borrow a stock to be able to sell it short and the market for borrowing stocks is not a centralized market. Therefore, according to Lamont and Thaler (2001), borrowing can be difficult and even impossible for many equities (stocks with low market capitalization for example). Illiquid stocks are also difficult to short.

According to Lamont and Thaler (2001) arbitrage does not eliminate mispricing due to short sale constraints and this may cause momentum. Lamont and Thaler argue that shorting costs are extremely high or shorting may simply be impossible and therefore eliminating exploitable arbitrage opportunities which in turn may cause momentum. A defiance of the law of one price is the background for this statement. The driver of the law of one price is arbitrage, which give arbitrageurs the motivation to eliminate defiance of the law of one price. Arbitrageurs react to information which affects the fundamental value, but due to high shorting costs they do not act strongly enough to drive prices down to the right value. It is important to note that short selling constraints do not explain overpriced stocks. To explain this, we need irrational players to bid up the prices beyond reasonable. Hence, according to Lamont and Thaler, two primary issues emerge: both trading costs and irrational market participants are necessary for mispricing.

According to Chan and Lakonishok (1995) average transaction costs for small firms are approximately 3% while Carhart (1997) estimate transaction costs to be around 0,95%. Lesmond Schill and Zhou (2001) find that there is little hold of transaction costs lower than 1,5% for every transaction since a momentum strategy pick stocks with high transaction costs. In Norway, due to a illiquid market, there may exist an even larger spread than in the findings of Lesmond Schill and Zhou which built their work on Jegadeesh and Titman's NYSE/AMEX research.

4. Previous Research

Thus far, finding that either indicate that markets are inefficient or that we have an inaccurate asset pricing model. For example, findings of the momentum effect did not seem to be important until the 1980's since the support of efficient markets stood strong in academic circles. In 1978, Jensen famously wrote "I believe there is no other proposition in economics which has more solid empirical evidence supporting it than efficient markets". But then in the 1980s, behavioral finance as an alternative approach to efficient markets was introduced. While the traditional approach was based on assumptions that individual participants in the market act rationally and utilize all available information, behavioral finance suggests that individuals does not act rationally, but are affected by a set of cognitive biases which leads to systematic errors and hence to suboptimal decisions (Shleifer 2000). In other words, behavioral finance helps explain why markets may not be efficient and consequently why prices in financial markets may not equal their fundamental value. Empirical evidence supporting this approach is found by amongst others DeBondt and Thaler (1985) and Jegadeesh and Titman (1993).

4.1 Previous international research

Some of the most important works concerning the momentum and mean reversal strategies are written by amongst others, Jegadeesh and Titman (1993), DeBondt and Thaler (1985) and Rouwanhorst (1998).

Jegadeesh and Titman (1993) find that the profitability of buying stocks that have done well in the past and selling stocks that have performed poorly in the past (over three to twelve months holding periods) is not due to systematic risk or to delayed stock price reactions to common factors such as the January effect. The evidence Jegadeesh and Titman find is consistent with delayed price reactions to firm specific information. They find however, that these returns are decreasing over longer horizons and that the first month following the formation date, which means that they found evidence of mean reversion over longer horizons than one year and also the first month.

Jegadeesh and Titman find that the best strategy selects stocks based on their return during the twelve previous months and then holds the portfolio for three months (J12:K3). When there is no time lag between the formation period and the holding period this strategy yields a profit of 1.31% per month.

Jegadeesh and Titman (2001) find that the momentum effect found in 1993 continued in the eight subsequent years, which they conclude provides some assurance that the momentum effect is not entirely a consequence of data mining. Also, they evaluate different explanations for the momentum effect and find evidence which supports the prediction of behavioral finance models which suggests that the momentum effect is due to overreactions in the market rather than the Conrad and Kaul (1998) hypothesis.

DeBondt and Thaler (1985) examine whether or not stock markets overreact to unexpected and dramatic news events. They find that in accordance with the overreaction hypothesis that past losers tend to outperform past winners on a longer horizon (3-5 years), three years after the formation day DeBondt and Thaler find that past losers outperform past winners by as much as 25% even after adjusting for risk. In other words they find evidence of long time mean reversion. Their results also touch upon the January effect; they do not come up with a sufficent explanation for this effect, but find that portfolios of losers experience large January returns as late as five years after formation day. Further, their results support the price-ratio hypothesis that high price-earnings (P/E) stocks are overvalued and low P/E stocks are undervalued and that this effect is for the most part a Seasonality/January phenomenon.

Rouwenhorst (1998) examines twelve European countries including Norway in the period from 1978 through 1995 using Jegadeesh and Titmans method from 1993. Rouwenhorst’s main findings are that an internationally diversified momentum portfolio earns about 1% per month. This momentum effect is significant on a 5% level in all countries, except Sweden. It holds for all size deciles, but he finds that especially the small firms yield excess momentum returns. The outperformance lasts for periods up to one year before prices starts to reverse. Further, he finds that the momentum effect cannot be attributed to risk, when controlling for market risk and exposure to a size factor, the excess return from following the momentum strategy actually increases. The excess return also increases with the ranking period (J) and falls for longer holding periods (K) and both the winners and losers, are on average, smaller than the average of the complete sample.

Grinblatt and Keloharju (2000) analyze the Finnish stock market. They look at the behavior of various investor types and are primarily focused on which investor group reveals momentum behavior and which reveals the opposite. Grinblatt and Keloharju find that foreign, more sophisticated investors, tend to be momentum traders while domestic, less sophisticated investors, particularly households, tend to be reversal traders which means that they buy past losers and sell past winners. The degree of momentum behavior seems to be strongly correlated with the degree of sophistication of the investor types. They rank the various investors according to their degree of momentum behavior in the following descending order:

1. Foreign investors
2. Domestic nonfinancial corporations
3. Domestic Finance and insurance institutions
4. Government investors and nonprofit organizations
5. Households

The foreign investors which tend to be well capitalized financial institutions such as mutual funds, hedge funds and investment banks are the most sophisticated and therefore according to Grinblatt and Keloharju most likely to trade on momentum. They also find that the portfolios of foreign more sophisticated investors tend to outperform the domestic investors even after controlling for behavioral differences.

4.2 Previous Research on the Oslo stock exchange|

In 2007 Harald Myklebust conducted a study whether there exists momentum in the Norwegian stock market over the period 1984-2006. Myklebust (2007) finds that all the sixteen different time strategies that he tested yielded positive returns. Further, he finds that the highest return was achieved by investing in the portfolio with a ranking period of nine months and a holding period of twelve months (J9:K12). The lowest return was achieved by investing in the portfolio with a ranking period of three months and a holding period of three months (J3:K3). All his returns were increasing in the holding period; the longer the holding period the higher the return, except for the portfolio with a ranking period of six months, which achieved the highest return after a holding period of nine months (J6:K9).

Like Jegadeesh and Titman (1993), Myklebust finds that the strategy with a ranking period of twelve months and a holding period of 3 months (J12:K3) gives the highest monthly return, yielding 2.21%. The only strategy which does not yield a return over 1% is the (J3:K3) strategy.

Myklebust concludes that all strategies give significant positive returns, but not for all periods. The period from 1990 to 1994 did not yield significant returns. This is the period where the average return of the ten portfolios is lowest. Study of risk demonstrates that the winner portfolios which he names P1 always had a greater average market size than the loser portfolios, P10 and that the beta values were equal or marginally higher in the losing portfolios. He then concludes that the zero investment portfolios (P1 – P10) did not have any extra market risk or a higher share of small companies.

In Kloster-Jensen's 2005 study of momentum on OSE over the period 1996-2005, a momentum strategy which combines a long position in the winning portfolio combined with a short position in the losing portfolio is found to yield significant positive returns. According to Kloster-Jensen, there is reason to believe that stock returns are to a certain degree predictable. His results also show that the momentum effect is stronger and lasts longer for the loser portfolios; it is the short selling of the loosing portfolios which generates the largest share of the momentum profit.

Kloster-Jensen then adjusts for systematic risk and finds that the difference in systematic risk explains almost the whole momentum effect. Further he finds that the winner portfolios contain small stocks and stocks with a low book-to-market value (B/M) while the loser portfolios contain small stocks and stocks with a high B/M value.

Kloster-Jensen concludes that abnormal returns from following a momentum strategy to a large extent are caused by compensation for taking on added systematic risk.

5. Data Material

We first examine an extensive set of data two determine the degree of statistically significant momentum in the market, that is the theoretically possible excess return an investor could earn from being a momentum trader in the Norwegian market. In the second part of our study, “the best strategy portfolio”, we focus on possible economic benefits of following a momentum strategy. To maximize the robustness of our study we use two different sets of data when working towards these two different objectives.

5.1 Large data sample to test the theoretical momentum effect

Our data is collected from “Børsdatabasen” at the Norwegian School of Economics and Business Administration. The data available from Børsdatabasen stretches back to 1984, but at this time index data for Oslo Stock Exchange (we use Oslo Stock Exchange All-share Index, OSEAX) has not been verified as controlled and reliable and we have therefore been instructed to limit our data to contain observations from the start of 1996 (Helge Flataker, Børsprojektet at NHH, 2008). Also, the number of stocks available diminishes as we go back in time. Consequently our sample data spans from the beginning of 1996 to the end of 2007. This gives us a total number of 598 stocks during the period. Some of these stocks have only been listed during a relatively short period of time and some are illiquid and lack trading days. The lack of trading days might lead to serial correlation in portfolio returns. One way to overcome the problem of missing trading days is not to incorporate stocks in the study that lack observations during the period. This has been done in earlier research of momentum in the Norwegian stock market Kloster-Jensen (2005) and Myklebust (2007). However, this approach would leave us with no more than approximately 70 stocks. The numbers of stocks are important for two main reasons: first, in order to establish whether or not there is momentum present we want to have as many stocks as possible to choose from when forming our winner and loser portfolios. Second, to minimize the idiosyncratic risk we want the selected portfolios to contain as many stocks as possible. This is a balance between forming large portfolios with little idiosyncratic risk, but less evidence of momentum, or smaller portfolios with higher momentum but possibly more idiosyncratic risk. We therefore have chosen to work with all 598 available stocks. When constructing the winner and loser portfolios, all stocks with available returns data in the J month foregoing the formation date are included. This is in-line with the method used by Jegadeesh and Titman (1993) and minimizes the problem with missing trading days while still allowing for a broader set of observations. Also, if we only accounted for the 70 stocks that are being traded during the entire period, our results would be affected by "survivorship bias" (Elton and Gruber, 1996). Companies performing relatively poorly are more likely to generate extreme results by either going bankrupt or turning around their business. If we only kept the poor performers that managed to turn around their business and excluded the ones that went bankrupt, it would affect the result of our test. From a practical point of view, a trading strategy based on the results from a study that excludes observations from stocks that have not made it through the whole testing period would imply that investors could predict which stocks that would be de-listed or not traded at all (Grundy & Martin, 1998).

To obtain a solid set of observations without excess noise we have used monthly data. As our risk-free interest rate we have used the various NIBOR's (Norwegian Inter Bank Offered Rate) that corresponds to our holding periods. That is, the three month NIBOR for portfolios with a three month holding period (K=3) and the six month NIBOR for portfolios with a six month holding period (K=6) and so on. We use generic adjusted stock prices: generic simply means that in case of missing observations the last known price is used. An adjusted stock price is a price that accounts for the fact that some changes in the price do not affect the real value to the investor. When calculating returns, one should use adjusted stock prices to measure the real change in value to the investor. The adjustments are transferred backwards so that the last adjusted price is equal to the nominal price. The stock prices are adjusted for dividends, splits and other events that dilute existing stocks.

5.2 Dataset "best strategy portfolio"

This part of the study is also based on the data from "Børsdatabasen" and the same rules of selection apply when we chose the time period to investigate, which consequently is the same as for the previous part. Again, we use monthly data and generic stock prices and the risk free-rate is the NIBOR corresponding to our holding periods. However, since we in this part of the study focus on the practical and economical implications of following a momentum strategy in the Norwegian stock market, we have a new set of selection criteria when picking the stocks to work with. We want to exclude the smallest and lowest priced stocks to secure that our results are not triggered mainly by illiquid and small stocks or by bid-ask bounces. Jegadeesh & Titman (2001) find, when examining NYSE and Nasdaq stocks, that the results are the same with or without a USD5 price screen except in the Januaries; "The low-priced stocks exhibit large return reversals in January and, as a result, the momentum strategies earn larger negative returns in January if these stocks are included". The data used for the "best strategy portfolio" have been filtered by the following conditions:

- The market value must at all times exceed NOK10m
- Close price must always exceed NOK10
- The stock must have been traded for a minimum of three years

This leaves us with a set of 123 stocks during the sample period spanning from the start of 1996 to the end of 2007.

6. Methodology and models

The methodology in our research is founded on previous studies by De Bondt & Thaler (1985), Jegadeesh & Titman (1993) and Jegadeesh & Titman (2001). The method aims at testing how well stock prices reflects available information and if there is an under or over-reaction to new information. The results derived are a product of the model, and restricted by the limitations of the model.

6.1 Methodology when testing for the theoretical momentum effect

In the first part of the study our main focus was to determine if there was statistical proof for momentum in the Norwegian stock market, and if so, which theoretical abnormal returns one could earn by following a momentum strategy. We also touch on the matter of economical significance by adjusting for transaction costs. We further examine this topic in our “best strategy portfolio” section where we operate with another set of data.

We use four time horizons called J during which the formation of the portfolios takes place based on the stock returns during these formation periods. J could be 3, 6, 9 or 12 meaning that the stocks are sorted during a 3, 6, 9 or 12 month period, we then buy the stocks that have had the highest returns and sell the once that have had the lowest returns and thereby establish portfolios. After the formation period follows the holding period called K, during which we hold the portfolios for 3, 6, 9 or 12 months. In total there are 16 individual J/K strategies formed by a formation period (J) and a holding period (K). Jegadeesh & Titman (1993) divide the stock market in deciles with the lowest past return decile being portfolio P1, the loser portfolio, and the highest past return decile being portfolio P10, the winner portfolio. Unlike Jegadeesh & Titman (1993) we have chosen to have a fixed number of stocks in every portfolio throughout the sample period even though the number of available observations varies over time. This is because we want to ensure that we have enough stocks to reduce idiosyncratic risk even in times of few observations. During the period from 1996 to the end of 2007, measured monthly, we had an approximate average number of 150 available observations of returns. Based on this we chose to always have 15 stocks in both the winner and the loser portfolio constituting approximately 10% each of the average number of observations. The portfolios inbetween the winner and the loser are not formed. The individual stocks included in the portfolios are equally weighted; we do not weight stocks relative to their market size.

We follow a "buy and hold" strategy were we buy the winner and sell the loser portfolio at the formation date and at the end of the holding period we terminate our holdings. At this point if $J \leq K$ we buy a new winner and sell a new loser based on the preceding formation period. If, on the other hand, $J > K$ we wait for the formation period, initiated at the same time as our last holding period to end and then we start over with new portfolios. An alternative to this strategy would be to operate with overlapping portfolios. Overlapping portfolios would give us more observations but when following a strategy with overlapping portfolios one uses the same returns multiple times which may cause autocorrelation. Consequences of autocorrelation are similar to those of heteroscedasticity. The coefficient estimates derived using ordinary least squares linear regression model are still unbiased, but they are inefficient even at large sample sizes; the standard error estimates may be incorrect. In the case of positive autocorrelation the standard error will be biased downwards (and the t-values overestimated). This would lead to a tendency to reject the null hypothesis even when it is correct (Brooks, 2002). In our case, this can lead to a remarkably high momentum effect.
We will however expand our tests to include overlapping portfolios when we further examine our "Best-strategy portfolio".

In order for a share to be considered for the holding period it needs to have returns available for all months of the preceding formation period. If a stock is delisted during the holding period, Jegadeesh & Titman (1993) invests the amount from the last available trade in the appropriate index. We have chosen a different approach when this problem occurs. We believe that stocks having outperformed the market during the formation period by such extent that they make it to the winner portfolio are less likely to disappear (during the following holding period) because of bankruptcy compared to stocks in the loser portfolio. Using the same argument, a stock having underperformed is less likely to be de-listed for a "positive reason" (e.g. acquired with a premium) compared to a member of the winner portfolio. Even though there might be exceptions to this theory, and albeit one could argue that we add to an eventual momentum effect by choosing this approach, we still believe that it is more correct to simply invest the amount from the last available trade in the next stock on the list. That is the stock with the sixteenth highest accumulated return during the formation period as replacement for a de-listed stock in the winner portfolio and the stock with the sixteenth lowest accumulated return as a replacement for a delisted stock in the loser portfolio, and so on.

Jegadeesh & Titman remove stocks with a market value that places them among the 10% smallest companies on NYSE and also stocks prices below USD5 at the time of portfolio formation. Since we are testing stocks listed on Oslo Stock Exchange we are dealing with fewer observations and therefore we wish to include all possible stocks. Our approach has several downsides such as the risk of the results being driven by illiquid stocks and large relative gaps between bid and ask prices. Therefore it should be viewed as a theoretical approach where the results might not be in line with what an actual investor could expect to achieve. The results that turn out to be statistically significant might not be economically significant.

6.1.1 Excess return (on the risk-free asset and the OSEAX)

All stocks selected for the portfolios are equally weighted regardless of their market share and price. We have calculated logarithmic returns because of its statistical advantages.

$$\boldsymbol{r_{i,t} = \ln(\frac{P_{i,t}}{P_{t-1}})} \qquad\qquad \boldsymbol{r_{m,t} = \ln(\frac{P_{m,t}}{P_{t-1}})}$$

$r_{i,t}$ is the monthly logarithmic return to stock *i* at time t, and $r_{m,t}$ is monthly logarithmic return to the market (measured as Oslo Stock Exchange All-share Index (OSEAX)) at time t. At the day of formation of the portfolios the stocks are sorted based on their cumulative return (cr) over the formation period J:

$$\boldsymbol{cr_i = \left(\prod_{t=-j}^{0}(1 + r_{i,t})\right) - 1}$$

Then the return of a portfolio of equally weighted stocks can be calculated. The 15 stocks with the highest *cr* will constitute the winner portfolio (*P=W)* and the 15 stocks with the lowest *cr* will form the loser portfolio (*P=L)*:

$$\boldsymbol{cr_{P,t} = \frac{1}{N}\sum_{i=1}^{N} cr_{i,t}}$$

$cr_{P,t}$ is the cumulative return of portfolio *P* at time t and *N* is the number of stocks in the portfolio (*N*=15).

Our first measurement of the portfolios return is against the market return. This is done by a non risk-adjusted model. We calculate the cumulative return to portfolio P $(cr_{P,K,t})$ over the holding period K and also the cumulative market return $(cr_{m,K,t})$ over the same period:

$$\boldsymbol{cr_{P,K,t} = \frac{1}{N}\sum_{i=1}^{N}\left(\left(\prod_{t=1}^{K}(1+r_{i,t})\right)-1\right) \qquad cr_{m,K,t} = \left(\prod_{t=1}^{K}(1+r_{m,t})\right)-1}$$

We then calculate the excess return for portfolio P on the market over the holding period K $\left(cR_{p,K,t}\right)$ by subtracting the cumulative market return for the same period K.

$$\boldsymbol{cR_{P,K,t} = (cr_{P,K,t} - cr_{m,K,t})}$$

Next, we calculate the cumulative monthly excess return (cmR) for the whole period from the beginning from 1996 to the end of 1997 $cmR_{P,K,T}$:

$$\boldsymbol{cmR_{P,K,T} = \frac{\sum^{T}\left(cR_{p,K,t}\right)^{\frac{1}{K}}}{T}}$$

The size of T depends on how many holding periods that fits into the whole period i.e. a function of J and K (when operating with overlapping portfolios, in the best strategy portfolio, T is the number of months during the whole sample period minus the first formation period of six month). Finally, when this process is carried out for both the winner portfolio *(P=W)* and the loser portfolio *(P=L)*, we calculate our zero sum “winner-loser portfolio” *(P=H)* by subtracting the loser portfolio from the winner portfolio:

$$\boldsymbol{cmR_{H,K,T} = cmR_{W,K,T} - cmR_{L,K,T}}$$

The winner-loser portfolio is a zero-sum portfolio since we buy the winners and sell the losers, a long and a short position with the combined investment of zero.

If the market is efficient on the weak-form stock prices already reflect the information in historic price- and turnover data which stipulates a null hypothesis saying that any given portfolio of ours has a cumulative monthly excess return equal to zero. If, on the other hand there is a positive autocorrelation in the returns any given portfolio of ours will have a cumulative monthly excess return different from zero.

$$\boldsymbol{HO_P}: \boldsymbol{cmR_{P,K,T}} = \boldsymbol{0}$$
$$\boldsymbol{HA_P}: \boldsymbol{cmR_{P,K,T}} \neq \boldsymbol{0}$$

If the latter is the case our winner portfolio will have a *cmR* greater than zero and our loser portfolio will have a *cmR* less than zero and the winner-loser portfolio, shorting the loser and buying the winners, will have a *cmR* greater than zero, i.e. the hypothesis for the winner-loser portfolio will be:

$$\boldsymbol{HO_P}: \boldsymbol{cmR_{H,K,T}} = \boldsymbol{0}$$
$$\boldsymbol{HA_P}: \boldsymbol{cmR_{H,K,T}} > 0$$

To test our hypothesis we follow the lead of Jegadeesh & Titman and use the t-test. The t-test assess whether the mean of two groups are different from each other (statistically different). The t-value that we present in the results is the coefficient divided by its standard error. The R^2, presented in some results, is the coefficient of determination adjusted for degrees of freedom.

As explained in earlier chapters one should bear in mind that to conclude that markets are not efficient in the weak form one needs to operate with a perfect market equilibrium model i.e. market efficiency cannot really ever be rejected.

6.1.2 Risk-adjusted performance

Our second test accounts for risk when measuring the momentum effect. The most common risk adjusting model is the CAPM and this is also the first model that we will use in this part of our study. Investors are usually said to be risk averse, they need to be compensated for the time value of money and for risk. In the CAPM the time value of money is represented as the risk free rate which is the return an investor will be given over a period of time on a theoretical risk-free investment. The investor also demands compensation for any non-diversifiable risk that he takes on. Diversifiable risk, or idiosyncratic risk as it is also called, is firm-specific and can be diversified away by spreading the investment on several securities and for that reason the investor will not be compensated for bearing this kind of risk. The non-diversifiable risk on the other hand can be thought of as external factors that affects the whole market such as macro shocks or business cycles i.e. factors that cannot be eliminated by spreading the investment on several securities. Different assets will be more or less sensitive to this kind of market risk and should yield a return thereafter. The CAPM measures the non-diversifiable risk by the beta coefficient (β) which is the sensitivity of the asset's return to the markets return. The market beta is one; an asset beta of more than one indicates that the particular asset fluctuates more than the market and vice-versa.

$$\boldsymbol{\beta_{P,m}} = \frac{\boldsymbol{Cov(r_P, r_m)}}{\boldsymbol{Var(r_m)}}$$

The CAPM equation:

$$\boldsymbol{E(r_P) = r_f + \beta_{P,m}(E(r_{m)} - r_f))}$$

$\boldsymbol{r_P}$ is the return of portfolio *P*, $\boldsymbol{r_f}$ is the risk-free rate and $\boldsymbol{r_m}$ is the market rate of return. The difference between the expected market rate of return and the risk-free rate is known as the market premium or the risk premium.

To estimate whether a portfolio has earned an abnormal return, that is, an extra return compared to the theoretically suitable rate of return determined by CAPM, we add a new measurement known as Jensen's alpha (α).

$$\boldsymbol{\alpha_P = E(r_P) - (r_f + \beta_{P,m}(E(r_{m)} - r_f)))}$$

With some alterations to this expression we can estimate the performance by regression analysis, where $\boldsymbol{\varepsilon_{P,t}}$ is an observational error, also known as noise:

$$\boldsymbol{r_{P,t} - r_{f,t} = \alpha_P + \beta_P(r_{m,t} - r_{f,t}) + \varepsilon_{P,t}}$$

The null hypothesis is; $HO\colon \alpha = 0$ and the alternative hypothesis will be $\boldsymbol{\alpha_W} > 0$ for the winner portfolio, $\boldsymbol{\alpha_L} < 0$ for the loser portfolio and for the winner-loser portfolio; $\boldsymbol{\alpha_H} > 0$.
Like Jegadeesh & Titman (1993) we extend our test of risk-adjusted performance to include an adjustment for size or more specifically small minus big, SMB. We have on the date of formation sorted all stocks based on their market cap in ascending order and calculated accumulated logarithmic returns from the formation period J (calculations same as above). Observations are created by dividing these returns at the median and subtracting the half with "big" market capitalization from the half with "small" market capitalization, consequently we end up with observations based on small minus big stocks by market capitalization. In the regression this shows up as a new factor in a two-factor model:

$$r_{P,t} - r_{f,t} = \alpha_P + \beta_P(r_{m,t} - r_{f,t}) + \gamma_P(SMB_t) + \varepsilon_{P,t}$$

The null hypotheses and the alternative hypotheses will be the same as for the risk-adjusted one factor model above.

6.2 Best strategy portfolio

As our best strategy portfolio we have chose the J6K6-strategy. In the results we will show that this actually isn't the portfolio that earned the highest cumulative monthly return (compare J9K6) but it is the strategy most thoroughly examined by some of our predecessors and therefore provides the opportunity of comparison with earlier research. In this part of the study, our focus shifts from testing the Norwegian stock market for statistical proof of momentum to actually proving whether or not it is economically feasible to follow a momentum strategy.

We operate with a new set of data and to examine the robustness of the momentum effect we extend our test of risk-adjusted performance to include a third factor; book-to-market value (i.e. the Fama and French three factor model). Now, we form portfolios both using overlapping formation and holding periods as well as non-overlapping periods as before. Overlapping formation means that every month a new formation period starts and overlapping holding means that every month we terminate a portfolio that we have held for the past six month and form a new portfolio based on the past six-month formation period results. Consequently, we hold several portfolios at all times, rebalancing every month by terminating one portfolio and forming one portfolio. The winner portfolio and the loser portfolio are formed using the ten best performing stocks and the ten worst performing stocks respectively. We have decreased the number of stocks in every portfolio since the total dataset contains fewer stocks. The downside with this is that by having fewer stocks in a portfolio we are more exposed to idiosyncratic risk.

In this part of the study we start of by presenting descriptive data in order to uncover patterns among the actual stocks that have made it to the winner and loser portfolios. We check whether any sectors are over or underrepresented among winners or losers.

The method for testing for momentum, without risk adjustments, is the same as for the previous part and so is the first risk-adjusting test, the CAPM. Out third test however, differs from the previous part. Here we use a three factor model developed by Fama & French (1993). This model ads a factor to our previous two-factor model. Third factor adjusts for book-to-market ratio, HML. HML is a differential portfolio created by dividing the list of stocks at the median sorted by the stocks book-to-market value. The portfolio is formed by buying stocks with a high book-to-market value (so called value stocks) and shorting stocks with a low book-to-market (so called growth stocks). The factor measures the historical excess return for value stocks over growth stocks, HML stands for high minus low. The rest of the terms in the below expression are equal to the two-factor model earlier described.

$$\boldsymbol{r_{P,t} - r_{f,t} = \alpha_P + \beta_P\left(r_{m,t} - r_{f,t}\right) + \gamma_P(SMB_t) + \lambda_P(HML_t) + \varepsilon_{P,t}}$$

Furthermore, we analyze sub periods. Based on the performance of the overall market, we identify business cycles during our test period and then test the momentum for boom and bust periods individually.

We have also added to the robustness by testing for seasonality through a closer examination of the January returns in our data sample. This is done by excluding the returns from January months from one set of portfolios and excluding the returns from all months except January for another set of portfolios.

Our final study is founded on previous research by Grinblatt and Keloharju (2000) on the behavior of different investor types. We calculate moving averages excess returns for different durations to discover eventual trends in momentum over time when following the J6K6 strategy. We do the same monthly moving calculations for the t-value to better grasp the significance of the returns. Then we compare our results to the development in investor types on the Oslo Stock Exchange during the time period.

7. Results

The results are presented in accordance with the objectives of their respective tests. First, we look at the theoretical excess return derived from our large data sample of 598 stocks. In the second part of the results, “the best strategy portfolio” we scrutinize the economic gains that an investor could earn from being a momentum trader in the Norwegian market. Here we also present descriptive data and the evidence we have found on seasonality, trends and more.

7.1 Results from testing for theoretical momentum (598 stocks)

7.1.1 Raw returns

From Table 1 it can be seen that every winner-loser portfolio yields a positive return, every strategy however, is not statistically significant at a 5% level. Therefore we cannot with 95% certainty reject the null hypothesis. We observe however, that nine of our portfolios yield significant excess positive returns relative to the benchmark while the other seven portfolios also yield positive return although not significant at a 5% level. Therefore we conclude that it appears to be profitable to follow a momentum strategy in the Norwegian market. This agrees with the conclusions of Jegadeesh and Titman (1993) although they find that every portfolio except from the J3:K3 portfolio is statistically significant.

Table 1

J	K	3	6	9	12
3	Sell loser	-0,07703	-0,20327	-0,24286	-0,11771
		-2,58	-4,61	-3,58	-0,64
3	Buy winner	0,00593	-0,11998	-0,01223	-0,01525
		0,31	-1,42	-0,21	-0,10
3	**Winner - loser**	**0,08297**	0,08330	**0,23063**	0,10246
		2,95	0,909	**3,69**	1,29
6	Sell loser	-0,06651	-0,12789	-0,22983	-0,10185
		-1,19	-3,71	-4,24	-0,85
6	Buy winner	0,01086	0,05109	0,08039	-0,03757
		0,23	1,43	1,09	-0,57
6	**Winner - loser**	**0,07737**	**0,17898**	**0,31022**	0,06427
		2,53	**3,78**	**4,62**	0,43
9	Sell loser	-0,16729	-0,26571	-0,20178	-0,18675
		-2,80	-4,72	-1,72	-1,45
9	Buy winner	-0,06811	-0,01393	-0,02102	0,02584
		-1,75	-0,19	-0,29	0,19
9	**Winner - loser**	0,09918	**0,25178**	0,18076	0,21259
		1,58	**3,23**	1,50	1,42
12	Sell loser	-0,02327	-0,12110	-0,10901	-0,17980
		-0,66	-4,19	-1,65	-1,68
12	Buy winner	0,08509	0,05148	0,08113	-0,02482
		1,98	1,15	1,12	-0,40
12	**Winner - loser**	**0,10836**	**0,17259**	**0,19014**	0,15497
		2,85	**2,93**	**2,23**	1,23

It is the loser portfolio that generates most of our momentum profit, while our loser portfolios yield between -2.33% (J12:K3) and -26.57% (J9:K6) our winner portfolios yields between -12% (J3:K6) and 8.5% (J12:K3). From our table we also see that the loser portfolios t-values are a great deal higher than the winner portfolios t-values. Eight loser portfolios are statistically significant while there are no significant winner portfolios. To exploit this it is necessary to short sell these losing stocks which may be costly and even impossible to realize so this may not be economically feasible. These findings agree with Hong, Lim and Stein (2000) and Jegadeesh and Titman (2001) which also find that most of the momentum effect is generated by the loser portfolios.

We see from the same table that the winner-loser portfolio that are based on the background of a ranking period of six months with a holding period of nine months (J6:K9) yield the highest return of 31.02% over the nine month holding period. This strategy is significant as well with a t-value of 4.62. Not surprisingly, we also see that returns increase with the holding period in the portfolios that are statistically significant. The J6:K3 portfolio is the portfolio that yields the lowest statistically significant return of 7.73%, with a t-value of 2.53.

According to Chan and Lakonishok (1995) average round trip transaction costs for small firms are approximately 3 % while Carhart (1997) estimate round trip transaction costs to be around 0.95%. Since The Oslo Stock exchange is comprised of more “less liquid” and smaller stocks, and since the investors are fewer, which implies that the market might be less efficient compared to large international markets such as the NYSE and Nasdaq, we have decided to assume a round trip transaction cost of 4% when working with the sample of all 598 stocks. This is fairly high, but considering the arguments above, and that we have to short sell the losing stocks, we find it reasonable. If we review the results above with this insight we find that the winner-loser portfolio yielding the lowest return (the J6:K3-portfolio) with a statistically significant return of 7.73% is no longer statistically significant after adjusting for transaction costs with a return of 3.57% after 3 months (t-value 1.17). Our best performing portfolio (the J6:K9-portfolio) yields a return of 31% over the nine months holding period before adjusting for transaction costs and a 26.4% significant return (t-value 3.93) after adjusting for transaction costs. In total, after adjusting for transaction costs we have four portfolios which still yield significant returns; the other five are still positive. We conclude that although transaction costs take away some of the profit it does not take away all of our excess returns. These results differ from Carhart (1997) which concludes that transaction costs takes away the excess returns from following a momentum strategy.

It might also be interesting to compare the monthly returns, depicted in Table 2:

Table 2

J	K	3	6	9	12
3	Winner - loser	**0,0269**	0,0134	**0,0233**	0,00816
		2,95	0.909	**3,69**	1.29
6	Winner - loser	**0,0252**	**0,0278**	**0,0305**	0,0052
		2,53	**3.78**	**4.62**	0.427
9	Winner - loser	0,032	**0,0382**	0,01863	0,0162
		1,58	**3,23**	1,5	1.42
12	Winner - loser	**0,0349**	**0,0269**	**0,0195**	0,0121
		2.85	**2.93**	**2,23**	1.23

We see from this table that J9:K6 performs best with a significant positive return of 3.82%. While J12:K3 and J6:K9 yield the second and third highest returns respectively. Jegadeesh and Titman (1993) and Rouwenhorst (1998) find that J12:K3 which we rank as our second best portfolio is the most profitable strategy, while Kloster-Jensen (2005) finds that the the J6:K6-portfolio yields the highest profit. Similar to Kloster-Jensen, we find that it is more profitable to hold the portfolios for a short horizon, in other words, the lower the holding period the higher the monthly return. This can be interpreted as a sign of long time reversal. These findings are consistent with the findings of Jegadeesh and Titman (1993) which suggest that a behavioral model rather than the Conrad and Kaul (1998) hypothesis explains momentum. This is because behavior models of overreaction predict long time reversals, while the Conrad and Kaul hypothesis predicts that the profits from the momentum strategy should be equally positive in any subsequent period.

Adjusted for transaction costs our top performing monthly return portfolio (J9:K6) yields an excess return on the market of 3.2% per month. Our worst performing portfolio (J12:K9) yields a return of 1.5% which is not statistically significant.

7.1.2 Adjustment for market risk - CAPM

In this section we want to test whether the momentum effect found in the previous chapter is still present after adjusting for systematic risk using the capital asset pricing model CAPM.

Table 3 shows a ranking period of three months and we see that none of the winner alphas, three of our loser alphas, and two of our winner–loser alphas are significant.

Table 3

J=3	K =	3	6	9	12
	α	**0.00668866**	**-0.0675808**	**-0.0502998**	**0.00922738**
	t-value	0.335	-0.788	-1.07	0.0549
Winner	β	**1.03576**	**1.40283**	**1.62056**	**0.770132**
	t-value	6.12	2.46	8.36	1.23
	R^2	**0.45463**	**0.22328**	**0.84309**	**0.142945**
	α	**-0.0644267**	**-0.155402**	**-0.276103**	**-0.0469676**
	t-value	-2.23	-3.93	-4.38	-0.231
Loser	β	**1.59702**	**1.62475**	**1.54189**	**0.335740**
	t-value	6.53	6.17	5.93	0.441
	R^2	**0.486266**	**0.644497**	**0.730273**	**0.02119**
	α	**0.0711154**	**0.0878211**	**0.225803**	**0.0561950**
	t-value	2,61	0.931	3.38	0.679
Winner - Loser	β	**-0.561265**	**-0.221922**	**0.0786714**	**0.434392**
	t-value	-2.43	-0.353	0.285	1.40
	R^2	**0.116419**	**0.00590196**	**0.00622714**	**0.179472**

Table 4 show a ranking period of six months, and the outcome of the alphas in terms of significance are the same as in Table 3, with three month ranking periods, except that we find one more strategy with a significant winner-loser alpha; that is the portfolio with the six month holding period.

Table 4

J=6	K =	3	6	9	12
Winner	α	**0.00664728**	**0.0453385**	**0.0498965**	**-0.0504876**
	t-value	0.157	1.35	0.695	-0.710
	β	**-0.103369**	**1.45314**	**1.49719**	**1.13995**
	t-value	-0.246	6.62	5.06	4.79
	R^2	**0.00286551**	**0.676042**	**0.663168**	**0.717881**
Loser	α	**-0.0701558**	**-0.136513**	**-0.263561**	**-0.182441**
	t-value	-1.32	-5.02	-5.89	-1.81
	β	**0.0457550**	**1.67969**	**1.54995**	**1.87326**
	t-value	0.0870	9.43	8.40	5.55
	R^2	**0.000360033**	**0.808976**	**0.844408**	**0.774188**
Winner - Loser	α	**0.0768031**	**0.181852**	**0.313457**	**0.131954**
	t-value	2.46	3.79	4.36	0.881
	β	**-0.149124**	**-0.226558**	**-0.0527586**	**-0.733307**
	t-value	-0.483	-0.721	-0.178	-1.46
	R^2	**0.0109707**	**0.0241263**	**0.00243084**	**0.191906**

For a ranking period of nine months, presented in Table 5, none of our winners, three of our losers and two of our winner–loser alphas are significant.

Table 5

J=9	K =	3	6	9	12
Winner	α	**-0.0204513**	**0.0425182**	**0.0134506**	**0.0542753**
	t-value	-0.571	0.588	0.187	0.360
	β	**2.17517**	**1.51605**	**1.44866**	**1.55505**
	t-value	3.60	3.70	4.90	1.47
	R^2	**0.4988**	**0.5136**	**0.6484**	**0.1528**
Loser	α	**-0.122583**	**-0.209356**	**-0.242704**	**-0.171974**
	t-value	-2.10	-3.93	-4.34	-1.19
	β	**1.48433**	**1.52742**	**1.67771**	**1.79306**
	t-value	1.51	5.06	7.29	1.78
	R^2	**0.1490**	**0.6636**	**0.8033**	**0.2087**
Winner - Loser	α	**0.102132**	**0.251874**	**0.256154**	**0.226250**
	t-value	1.55	3.11	2.57	1.33
	β	**0.690837**	**-0.0113700**	**-0.229051**	**-0.238004**
	t-value	0.622	-0.0248	-0.559	-0.200
	R^2	**0.0289**	**0.0000**	**0.0234**	**0.0033**

Our last risk-adjusted table, Table 6, with a ranking period of twelve months tells us that none of our winner, two of our loser and three of our winner–loser alphas are significant.

Table 6

J=12	K =	3	6	9	12
Winner	α	**0.0857865**	**0.0549521**	**0.0696686**	**0.0236642**
	t-value	1,9	1.02	0.965	0.352
	β	**0.858970**	**0.938962**	**1.31800**	**1.18701**
	t-value	1.41	2.04	4.70	5.28
	R^2	**0.1802**	**0.3162**	**0.7104**	**0.7556**
Loser	α	**-0.0235483**	**-0.151649**	**-0.123926**	**-0.171372**
	t-value	-0.636	-5.45	-2.04	-1.71
	β	**1.05514**	**1.53742**	**1.41393**	**1.62109**
	t-value	2,11	6.48	5.99	4.84
	R^2	**0.3312**	**0.8234**	**0.7995**	**0.7222**
Winner - Loser	α	**0.109335**	**0.206601**	**0.193594**	**0.195036**
	t-value	2,74	3.08	2.14	1.47
	β	**-0.196169**	**-0.598455**	**-0.0959320**	**-0.434079**
	t-value	-0.364	-1.05	-0.273	-0.977
	R^2	**0.0145**	**0.1086**	**0.0082**	**0.0958**

If we first review our alphas we find that none of our winner alphas are significant, while ten of our 16 loser alphas are significant and also ten of our winner-loser alphas are significant. If these risk-adjusted alpha values reported above are significantly positive it means that their respective portfolios have done better than the expectations according to the CAPM. On the other hand, if these risk-adjusted alpha values are significant negative it means that their portfolios have performed worse than what was expected according to the CAPM. We can therefore conclude that the loser portfolios are performing better than their expectations although not for every portfolio. The winner portfolios however are not significant; hence we cannot say whether or not they perform better than their expectations derived from the CAPM model.

Of our 16 winner-loser portfolios ten are significant on a 5% level and all alphas are positive. The alpha values have actually increased in twelve out of 16 portfolios which means that the excess return from following a momentum strategy increase when we adjust for systematic risk. We observe from Table 1, before we adjusted for systematic risk using the CAPM model, that the same winner-loser portfolios are significant except for J9:K9 which become significant positive first after we adjust for systematic risk. This indicates that the momentum effect is still very much present after adjusting for systematic risk. These results are similar to those of Rouwenhorst (1998) which studied the European market, he also finds that the excess return from following a momentum strategy actually increase after adjusting for systematic risk.

We find that all the betas for the loser portfolios except three are higher than the betas of the winner portfolios; hence the loser portfolio is more exposed to market risk. This difference is not statistically significant. Since the difference is not significant we cannot say that the momentum return from holding the winner-loser portfolio is due to differences in systematic risk (beta). Our conclusion that the momentum effect is not due to systematic risk is in line with the conclusion of Jegadeesh and Titman (1993). In contrary to our study Jegadeesh and Titman (1993) find that the winner portfolios are more exposed to market risk, although not statistically significant.

The winner portfolio betas are positive for every strategy but J6:K3, and significantly positive for every strategy except J3:K12, J6:K3, J9:K12 and J12:K3. This means that the winner portfolios tend to fluctuate in the same direction as the market. We see a tendency for the betas to increase with the holding period for all ranking periods except for the ranking period of nine months where it has a tendency to decrease.

The loser portfolio betas are significant for every strategy except J3:K12, J6:K3, J9:K3 and J9:K12 and all the betas are positive. This means that all the loser portfolios fluctuate in the same direction as the market. As for the winner betas, we also observe a tendency for the loser betas to increase with the holding period. What's more is that we see that the loser portfolios have larger betas in general than the winner portfolios which clearly indicate that the loser portfolios are more exposed to market risk?

The beta coefficients of the loser portfolios are higher than the betas of the winner portfolios in every strategy except for J3:K9, J3:K12 and J9:K3, this means that 13 out of 16 winner-loser portfolios have negative betas. This suggests that the majority of our winner-loser portfolios fluctuate against the market. However, only one of the winner-loser betas, the J3K3-beta, is significantly different from zero at a 95% confidence interval.

7.1.3 Two - Factor model

In this part we adjust for two factors; market risk as we did above and also a size factor, the SMB which denotes small minus big. In Table 7 we present the two-factor model returns with a ranking period of three months.

In Table 7 and Table 8 our results are very similar to the alphas and the betas adjusted only for systematic risk by the CAPM model that we presented earlier. Our SMB coefficients however are only significant for one winner–loser portfolio in Table 7, the J3:K3, and none of the winner loser portfolios in Table 8. This may be due to a lower number of observations for every holding period except for the three months holding period.

Table 7

J=3	K =	3	6	9	12
Winner	**α**	**0.0156202**	**-0.0820918**	**-0.0663721**	**0.0219569**
	t-value	0.758	-0.867	-1.12	0.100
	β1	**1.08915**	**1.39658**	**1.65029**	**0.784352**
	t-value	6.59	2.47	7.24	1.16
	SMB	**1.07970**	**-0.193131**	**0.379552**	**0.0116821**
	t-value	1.74	-0.632	0.450	0.0569
	R^2	0.498282	0.237405	0.84436	0.158752
Loser	**α**	**-0.0599913**	**-0.183384**	**-0.252494**	**-0.0151775**
	t-value	-2.32	-4.27	-3.46	-0.0573
	β1	1.76039	1.52476	1.73408	0.345151
	t-value	**8.49**	**5.95**	**6.19**	**0.423**
	SMB	3.31980	0.186643	1.50716	0.00801477
	t-value	4.27	1.35	1.45	0.0323
	R^2	0.644791	0.66395	0.775953	0.0248528
Winner - Loser	**α**	**0.0756115**	**0.101292**	**0.186122**	**0.0371344**
	t-value	2.83	0.995	2.30	0.348
	β1	-0.671234	-0.128178	-0.0837889	0.439201
	t-value	**-3.13**	**-0.211**	**-0.269**	**1.34**
	SMB	-2.24010	-0.379774	-1.12761	0.00366737
	t-value	-2.79	-1.16	-0.980	0.0367
	R^2	0.253528	0.0677159	0.0781859	0.197817

Table 8

J=6	K =	3	6	9	12
Winner	**α**	**0.0605175**	**0.0167712**	**0.0770307**	**-0.0572561**
	t-value	1.10	0.442	0.899	-0.416
	β1	**-0.00436040**	**1.47219**	**1.65140**	**1.15283**
	t-value	-0.0101	6.97	4.99	4.02
	SMB	**0.461632**	**-0.391887**	**1.28623**	**0.00790760**
	t-value	0.579	-0.757	1.05	0.00573
	R^2	0.0165198	0.159635	0.698221	0.736054
Loser	**α**	**-0.0146522**	**-0.152124**	**-0.284431**	**0.0226967**
	t-value	-0.215	-4.89	-5.09	0.132
	β1	0.174965	1.65689	1.52266	2.14194
	t-value	**0.327**	**9.57**	**7.07**	**6.01**
	SMB	0.683357	0.286513	-0.0615117	2.87239
	t-value	0.693	0.675	-0.0771	1.67
	R^2	0.0295598	0.822625	0.848967	0.830258
Winner - Loser	**α**	**0.0412472**	**0.168896**	**0.361462**	**-0.0799528**
	t-value	0.387	3.07	4.24	-0.289
	β1	-0.109217	-0.184698	0.128732	-0.989111
	t-value	**-0.305**	**-0.604**	**0.391**	**-1.72**
	SMB	1.64916	-0.678399	1.34774	-2.86448
	t-value	0.416	-0.906	1.11	-1.03
	R^2	0.0258956	0.0580362	0.0950015	0.27082

We observe the same tendency with very similar alphas and betas to the systematic risk-adjusted results in Table 9 as we did in Table 7 and 8. The J9:K3 portfolio has the only significant winner – loser SMB coefficient similar to what we observed in Table 7.

Table 9

J=9	K =	3	6	9	12
Winner	**α**	**-0.0132780**	**0.0673008**	**0.0346814**	**-0.0183974**
	t-value	-0.331	0.696	0.448	-0.102
	β1	**2.02646**	**1.48958**	**1.35665**	**1.47473**
	t-value	3.31	3.62	4.68	1.50
	SMB	**0.0125692**	**0.436329**	**0.0224577**	**-1.04769**
	t-value	0.0123	0.361	0.680	-0.767
	R^2	0.479072	0.54075	0.675578	0.217196
Loser	**α**	**-0.0704525**	**-0.153302**	**-0.245363**	**-0.122242**
	t-value	-1.60	-2.27	-4.08	-0.712
	β1	2.21172	1.58105	1.65437	1.92222
	t-value	**3.30**	**5.50**	**7.34**	**2.04**
	SMB	3.82461	1.05958	-0.00998034	0.689051
	t-value	3.41	1.25	-0.388	0.528
	R^2	0.630971	0.719612	0.822101	0.281319
Winner - Loser	**α**	**0.0571746**	**0.220602**	**0.280045**	**0.103844**
	t-value	0.965	2.06	2.64	0.532
	β1	-0.185264	-0.0914744	-0.297720	-0.447498
	t-value	**-0.205**	**-0.201**	**-0.750**	**-0.419**
	SMB	-3.81204	-0.623254	0.0324380	-1.73674
	t-value	-2.52	-0.465	0.717	-1.17
	R^2	0.34658	0.0177731	0.068513	0.1107

Table 10 which show a ranking period of twelve months is no exception and the numbers here are also very similar to the CAPM adjusted returns. Here, three out of four winner–loser alphas are statistically significant on a 5% level just like in Table 6 for the systematic risk-adjusted returns. As with a ranking period of three and nine months also the ranking period of twelve month only has a significant SMB coefficient for the three month holding period.

Table 10

J=12	**K =**	**3**	**6**	**9**	**12**
	α	**0.118611**	**0.0529878**	**0.0709086**	**0.00982450**
	t-value	2.45	0.973	0.802	0.129
	β1	**1.23818**	**0.925936**	**1.31574**	**1.21691**
Winner	t-value	2.32	2.30	2.72	5.13
	SMB	**2.55916**	**-0.632054**	**0.158490**	**-0.309814**
	t-value	1.47	-0.818	0.0807	-0.394
	R^2	0.415696	0.450685	0.724392	0.778021
	α	**-0.0321385**	**-0.150878**	**-0.147060**	**-0.151980**
	t-value	-0.729	-5.30	-2.03	-1.35
	β1	0.995063	1.47973	1.20970	1.51414
Loser	t-value	**2.04**	**7.03**	**3.05**	**4.32**
	SMB	-0.619210	0.176555	-0.891020	0.757374
	t-value	-0.391	0.437	-0.554	0.652
	R^2	0.428175	0.861323	0.822006	0.744016
	α	**0.150749**	**0.203866**	**0.217969**	**0.161804**
	t-value	4.14	3.02	2.01	1.09
	β1	0.243112	-0.553797	0.106037	-0.297228
Winner - Loser	t-value	**0.604**	**-1.11**	**0.178**	**-0.642**
	SMB	3.17837	-0.808609	1.04951	-1.06719
	t-value	2.43	-0.843	0.435	-0.696
	R^2	0.43186	0.17752	0.0341182	0.140901

Summed up the tables above show that nine out of our 16 winner-loser portfolios are statistically significant on a 5% level, and every winner-loser portfolio except from J6:K12 are positive. This suggests as our previous tests did, that there is a momentum effect in the Norwegian market.

Our beta coefficients for the winner and loser portfolios are mostly similar to those in the CAPM adjusted results. In other words the betas derived from our CAPM test are similar to those derived from the two factor model; hence our exposure to systematic risk is fairly similar measured with the two different models. Further, our winner-loser portfolio betas are still not significant except from the J3:K3-strategy. This tells us that the momentum effect is not explained by adjusting for systematic risk. We therefore conclude that the profitability of the strategy is not a compensation for systematic risk.

Our winner-loser portfolio SMB coefficients however are not as easy to interpret, six of our SMB coefficients are positive while ten are negative. Only three winner-loser portfolio coefficients are statistically significant on a 5% level, two are negative and one is positive. The low significance levels for the SMB coefficient and high positive significance levels for the alphas indicate that the SMB factor does not explain the momentum effect which is in line with the results of amongst others Rouwenhorst (1998). The negative SMB coefficients indicate that most of the winner-loser portfolios will react positive when large companies outperform small companies.

A low R^2 tells us that the model used does not explain much of the momentum effect. We have a rather low R^2 for the winner–loser portfolios. The R^2 varies from 1% to 43%. On average however this is higher than the R^2 derived from the CAPM model. This implies that the two factor model explains excess returns from following a momentum strategy better than the CAPM, but none of the models provide a very high degree of explanation.

7.2 Best strategy portfolio

7.2.1 Descriptive data (sector analysis)

Before presenting the momentum strategy results we have tried to identify and illustrate any over or underrepresentation from different sectors in our portfolios. It would have been interesting to test for momentum when following a strategy where one buys the sector that have had the highest past returns and shorts the sector with the lowest past returns. However, our sample of 123 stocks doesn't fully allow us to perform such a test since some sectors comprise over 20% of the total sample of stocks while others include less than 2% of the stocks, i.e. there would be a bias towards the sectors comprising more stocks when forming winner and loser portfolios, especially since our portfolios include ten stocks each or almost 10% of the total number of stocks.

111 stocks end up in the winner portfolio at least once and 103 stocks end up in the loser portfolio at least once during the sample period. In total 114 stocks from the total sample of 123 stocks either makes it to the winner or the loser portfolio one or more times during the sample period.

Table 11 shows the ten sectors defined by the Global Industry Classification Standard (GICS), used by Oslo Børs (Oslo Børs 2008), and their representation in our sample of stocks and our winner and loser portfolios. From the original data of 123 stocks (from Børsdatabasen) only 115 stocks have been sector classified. This is because the only information we have on the remaining eight stocks is a ticker, and unfortunately these tickers no longer exist. More than half of the 115 companies have been de-listed and for these companies we have done the sector classification ourselves, analogous to the GICS.

Some sectors stand out among the winner and loser portfolios. Financials are underrepresented on both the winner and the loser sides, implying that this sector is less volatile than the average sector. Energy and Information Technology (IT) are sectors that more often than average shows up among the winners, especially energy with an overrepresentation of 6.3%, as shown by the “Diff”-column (calculated as “%winner” minus “%total”). The loser portfolios tend to favor healthcare stocks and IT-stocks. The latter has a percentage representation difference compared to the whole sample by as much as 9.3% and is also a frequent inhabitant of the winner portfolio, implying that the sector is relatively volatile and also a relatively bad performer. However, almost half of the appearances of IT-stocks in the loser portfolio occurred during the bust-period also known as the IT-crash, a two and a half year period from the end of 2000 to the first quarter of 2003. In other words if we were to exclude this period from the sample the IT-shares would still be overrepresented in the loser portfolios, but to a less extent.

Table 11

	Total (115 companies)		Winner (127 portfolios)			loser (127 portfolios)		
	Nr	%	Nr	%	Diff	Nr	%	Diff
Industrials	29	25,2 %	279	24,0 %	-1,2 %	283	22,3 %	-2,9 %
Consumer discretionary	23	20,0 %	223	19,2 %	-0,8 %	231	18,2 %	-1,8 %
Financials	22	19,1 %	144	12,4 %	-6,7 %	162	12,8 %	-6,4 %
Energy	16	13,9 %	235	20,2 %	6,3 %	139	10,9 %	-3,0 %
Materials	7	6,1 %	40	3,4 %	-2,6 %	98	7,7 %	1,6 %
Information Technology	6	5,2 %	109	9,4 %	4,2 %	185	14,6 %	9,3 %
health care	4	3,5 %	64	5,5 %	2,0 %	101	8,0 %	4,5 %
Consumer staples	4	3,5 %	41	3,5 %	0,1 %	40	3,1 %	-0,3 %
Utilities	2	1,7 %	25	2,2 %	0,4 %	16	1,3 %	-0,5 %
telecommunication servic	2	1,7 %	2	0,2 %	-1,6 %	15	1,2 %	-0,6 %
SUM	115	100 %	1162	100 %	0 %	1270	100 %	0 %

7.2.2 Raw returns

From Table 12 we see that the J6K6-overlapping portfolio has an excess return on the market of approximately 4% over the holding periods in average, and this is statistically significant. The excess return is mainly derived from the short positions while the winner portfolio's excess return is low but positive which is in accordance with our previous findings and also the findings of Jegadeesh and Titman (2001) and Kloster-Jensen (2005). From an economic perspective we wish to determine if this strategy can be used in practice to earn a profit. Since we now operate with a dataset screened for small and illiquid stocks (i.e. stocks that will inflict lower transaction costs and that with greater ease can be shorted) we base our estimate for a round-trip transactions cost on Carharts (1997) estimates of 1% and add an "Oslo Stock Exchange premium" of 0.5%. This gives us a round-trip transactions cost of 1.5%. After transaction costs of forming and terminating the portfolio we are left with an excess return of approximately 3% over the six month period or a 0.5% excess return per month.

Table 12

N=127		Winner	Loser	Winner-Loser
α	**α**	**0.00470707**	**-0.0355166**	**0.0402237**
	t-value	0.487	-2.79	2.38
	t-prob	0.6273	0.0061	0.0189

The non-overlapping portfolio has the same tendencies and an excess return somewhat above the previous result, but none of the alphas are significantly different from zero.

Table 13

N=22		Winner	Loser	Winner-Loser
α	**α**	**0.00117718**	**-0.0455038**	**0.0466810**
	t-value	0.0648	-1.56	1.23
	t-prob	0.9490	0.1332	0.2318

7.2.3 Adjustment for market risk – CAPM

The results are similar to the previous non risk-adjusted test, but the excess return has actually increased which is consistent with our findings in the theoretical part. The Beta coefficient to the winner-loser portfolio is negative which implies that the portfolio moves in the opposite direction to the benchmark, but since it is not significantly different from zero we conclude that market risk does not explain the excess return of the winner-loser portfolio which is similar to our previous findings and to the findings of Jegadeesh and Titman (1993) and Myklebust (2007).

From the R^2 we also see that the movements of our winner-loser portfolio hardly at all is explained by the movements in the Benchmark while for the winner and loser portfolios around 70% of the variability is explained. The winner portfolio has a small but positive alpha, but it is the negative excess return of the loser portfolio that contributes the most to the winner-loser portfolios result. Adjusting for transactions cost we are left with an economic profit of approximately 3.15% over the six month holding period or an annualized gain of 6.3%.

Table 14

N=127		Winner	Loser	Winner-Loser
CAPM	**α**	**0.00764630**	**-0.0388544**	**0.0465007**
	t-value	0.761	-2.94	2.65
	t-prob	0.4480	0.0040	0.0091
	β	**0.942762**	**1.06500**	**-0.122239**
	t-value	17.6	15.1	-1.31
	t-prob	0.0000	0.0000	0.1925
	R^2	**0.713455**	**0.646864**	**0.0135484**

Similar to the non risk-adjusted test we see the same tendency for the non-overlapping and the over-lapping tests, but again we have no statistically significant excess returns. However with a t-prob of 16% we have a winner-loser portfolio excess return, adjusted for market risk, which measures almost 6% over a six month period.

Table 15

N=22		Winner	Loser	Winner-Loser
CAPM	**α**	**0.00451702**	**-0.0536627**	**0.0581797**
	t-value	0.233	-1.74	1.46
	t-prob	0.8184	0.0968	0.1609
	β	**0.938136**	**1.15113**	**-0.212991**
	t-value	8.48	6.56	-0.936
	t-prob	0.0000	0.0000	0.3604
	R^2	**0.782576**	**0.682858**	**0.0419663**

7.2.4 The Fama French Three factor model

When adjusting for Fama's and French's three factors we get an excess return for the winner-loser portfolio of 7.67% over the holding period which is an increase compared to when we only adjust for market risk exposure. These findings are similar to our previous findings and those of Rouwenhorst (1998) who finds that excess return from following a momentum strategy increase after controlling for market risk and exposure to a size factor. We find a monthly increase of approximately 0.25% comparable to that of Rouwenhorst (1998) of a little over 0.3% per month. Again the largest contribution comes from the loser portfolio, but the winner portfolio has a positive return though not significantly different from zero. The market risk coefficient is significantly different from zero for all three portfolios so the market risk does explain some of the excess return of the momentum trading strategy. The SMB coefficient is significant both for the loser portfolio and the winner-loser portfolio and does explain some of the excess return of the winner-loser portfolio. It seems that the loser portfolio is comprised of relatively small stocks and that it will react positive when small caps outperform large caps, also in line with the findings of Rouwenhorst (1998). The opposite goes for the winner-loser portfolio which has a short position in the loser portfolio.

We have no significant results from adjusting for book-to-market values. However tendencies of the coefficients imply that both the winner portfolio and the loser portfolio have an overweight of value stocks compared to growth stocks. The effect is larger for the loser portfolio which we short; hence the winner-loser portfolio has a negative HML factor, though not significantly different from zero. An adjustment for transaction costs would leave us with a profit of approximately 12.25% annually or slightly above 1% a month, given the six month holding period.

Table 16

N=127		Winner	Loser	Winner-Loser
FF3F	**α**	**0.00829941**	**-0.0684411**	**0.0767405**
	t-value	0.756	-5.37	4.29
	t-prob	0.4514	0.0000	0.0000
	β	**0.946774**	**1.25826**	**-0.311487**
	t-value	15.5	17.8	-3.13
	t-prob	0.0000	0.0000	0.0022
	SMB	**-0.111621**	**6.82728**	**-6.93890**
	t-value	-0.113	5.97	-4.32
	t-prob	0.9100	0.0000	0.0000
	HML	**0.641639**	**0.858059**	**-0.216421**
	t-value	0.666	0.767	-0.138
	t-prob	0.5067	0.4444	0.8906
	R^2	**0.714529**	**0.726747**	**0.143682**

For the non-overlapping portfolios only the beta coefficients for the winner and loser portfolios are significantly different from zero on a 5% significance level. However the alpha for the loser portfolio is significantly negative on a 10% level and the SMB Coefficient is also significant on the 10% level, implying that there is an overweight of small caps in the loser portfolio. Again we see a positive alpha for the winner-loser portfolio of almost 7%.

Table 17

N=22		Winner	Loser	Winner-Loser
FF3F	**α**	**0.00374939**	**-0.0660248**	**0.0697742**
	t-value	0.175	-1.97	1.59
	t-prob	0.8631	0.0640	0.1285
	β	**0.900214**	**1.22560**	**-0.325390**
	t-value	6.82	5.95	-1.21
	t-prob	0.0000	0.0000	0.2435
	SMB	**-0.612470**	**2.90655**	**-3.51902**
	t-value	-0.328	0.996	-0.921
	t-prob	0.7469	0.3323	0.3690
	HML	**-1.20122**	**-0.738852**	**-0.462368**
	t-value	-0.737	-0.291	-0.139
	t-prob	0.4704	0.7747	0.8911
	R^2	**0.789475**	**0.702638**	**0.0851203**

We cannot explain the momentum effect neither by the CAPM nor by the three factor model. Instead we have findings of higher excess returns when adding more “explanatory” variables to our model. As mentioned earlier Fama (1991) argue that market efficiency is not testable unless one has an accurate equilibrium model. Since we can't consider our models to be perfect equilibrium models the overall conclusion when adjusting for Fama and French's three factors is that our results seem to be objectives of the Joint-Hypothesis problem.

7.2.5 Seasonality

Previous research has documented a significant seasonality in momentum profits. Jegadeesh and Titman (1993 and 2001) reports that winners outperform loser in all month except January, when the losers significantly outperform the winners.

Our findings are in line with the ones of Jegadeesh and Titman. When forming portfolios over a six month ranking period and holding the portfolios for the subsequent six month our winner-loser portfolio earns an excess return of approximately 4.85% or 9.70% annually. The returns of the loser and the winner-loser portfolio are significantly different from zero at the 5% level, while the winner portfolio has a return close to zero.

Table 18

		All month except january		
N=126		**Winner**	**Loser**	**Winner-Loser**
α Seasonality	**α**	**-0.00462169**	**-0.0530815**	**0.0484598**
	t-value	-0.492	-4.42	3.07
	t-prob	0.6234	0.0000	0.0026

The next table shows the January returns, based on a six month ranking period. The loser portfolios significantly outperform the winners resulting in a negative excess return of the winner-loser portfolio of almost 6.8% per month, significant at the 10% level. One should note that the test contains few observations (N=10).

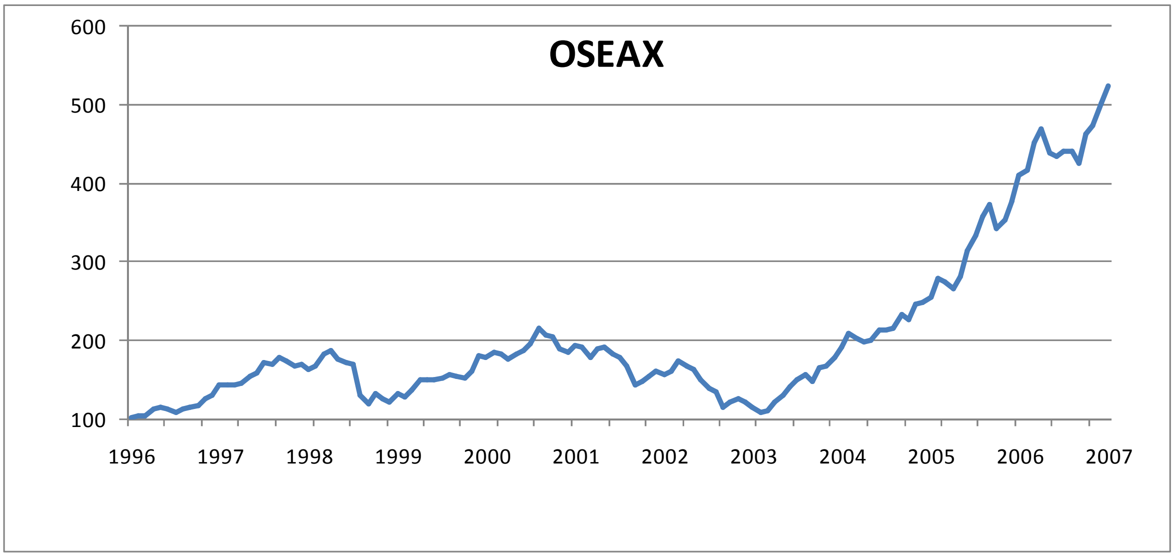
Table 19

		Only January		
N=10		**Winner**	**Loser**	**Winner-Loser**
α Seasonality	**α**	**-0.00705245**	**0.0608940**	**-0.0679465**
	t-value	-0.397	2.51	-1.89
	t-prob	0.7009	0.0332	0.0915

7.2.6 Business Cycles

Figure 1 shows the development in the benchmark (the OSEAX) over the sample period. We want to investigate the variation in momentum returns during business cycles. The first period we have defined ranges from 1996 to 2001. It's neither a boom nor a bust period, but more a period of two booms and one bust. The reason we have chosen not to further divide this period in three is that it would result in rather few observations per period. The second period is a bust period, the "IT-crash", stretching from 2001 to 2003 and the third and last period is the boom covering the rest of our main sample period.

Figure 1



During the first period we see results, though not significantly different from our earlier findings. The winner portfolio follows the same pattern as before but the loser portfolio has outperformed, even compared to the winner portfolio. Consequently the winner-loser portfolio shows signs of reversal (a negative alpha, but far from significant) on behalf of the loser portfolio.

Table 20

		1996-07-31--2000-12-29		
N=54		**Winner**	**Loser**	**Winner-Loser**
α Business Cycles	α	**0.0154401**	**0.0204180**	**-0.00497792**
	t-value	0.999	1.02	-0.196
	t-prob	0.3223	0.3101	0.8451

The second period, the bust period, is more in line with the results from the test for the whole sample period with a positive but not significant alpha for the winner portfolio and a negative and significant alpha for the loser portfolio. The excess return of the winner-loser portfolio is statistically significant and slightly above 6% for the six month holding period, about 1.5% more than for the whole sample period.

Table 21

	2000-12-29--2002-12-30			
N=25		**Winner**	**Loser**	**Winner-Loser**
α Business Cycles	α	**0.0168821**	**-0.0449349**	**0.0618170**
	t-value	1.32	-2.12	2.29
	t-prob	0.1997	0.0449	0.0311

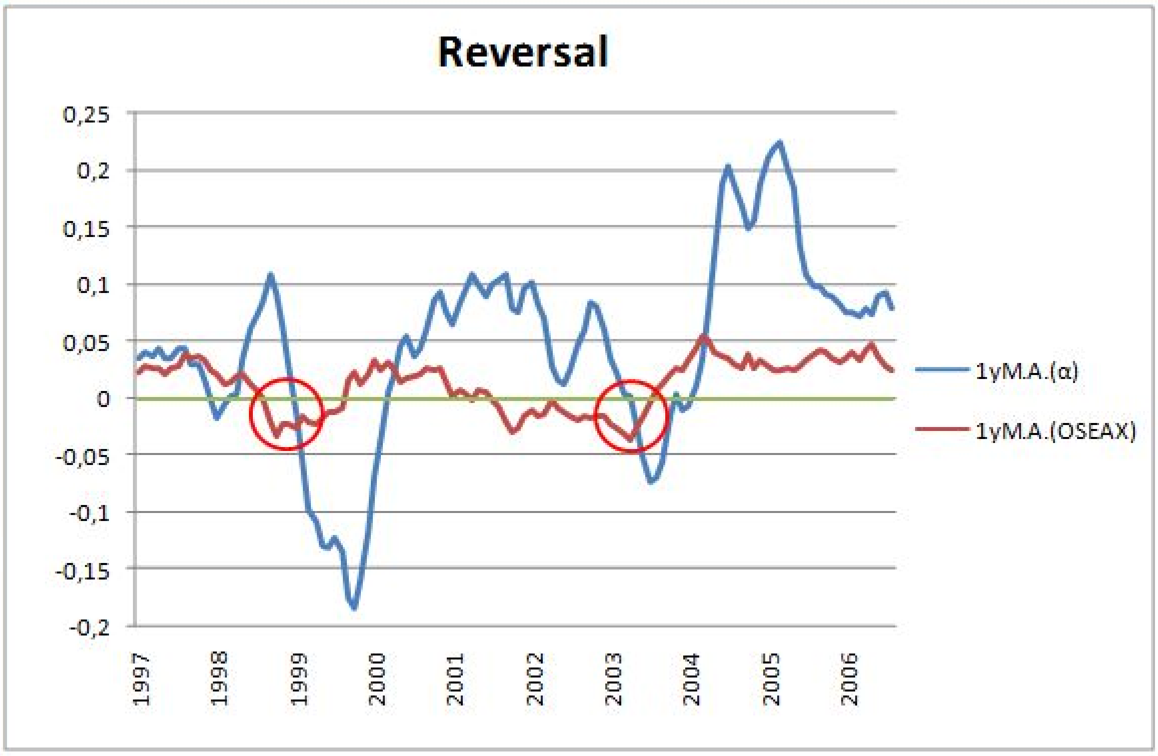
The last period, the boom period, shows a trend by further increasing the winner-loser alpha. This time around we get a significant excess return of more than 8% for the holding period, even though the winner alpha is slightly negative. It's the bad performance of the loser portfolios during this period that adds to the positive winner-loser result.

Table 22

	30.12.2002-31.01.2007			
N=50		**Winner**	**Loser**	**Winner-Loser**
α Business Cycles	α	**-0.0108723**	**-0.0953026**	**0.0844303**
	t-value	-0.644	-5.00	2.83
	t-prob	0.5226	0.0000	0.0067

To fully evaluate if there are any variations to the momentum effect in good times and bad times we have calculated a one year moving average for the winner-loser portfolio alpha (the average alpha over a twelve month period, moving one month ahead every month) and a one year moving average of the logarithmic returns to our benchmark, the OSEAX, plotted together in figure 2. An interesting fact is that we see dramatic reversals from holding our portfolios in the two periods subsequent to the two bust periods (the circled areas, also compare figure 1 for the basic index), where the alpha turns negative. According to Conrad and Kaul (1998) if risk exposure is the explanation to the positive excess returns of momentum strategies the profits from a momentum strategy should be the same in any post ranking period, in other words there should be no reversals. Our findings are more in line with the behavioral theory of overreaction.

Figure 2

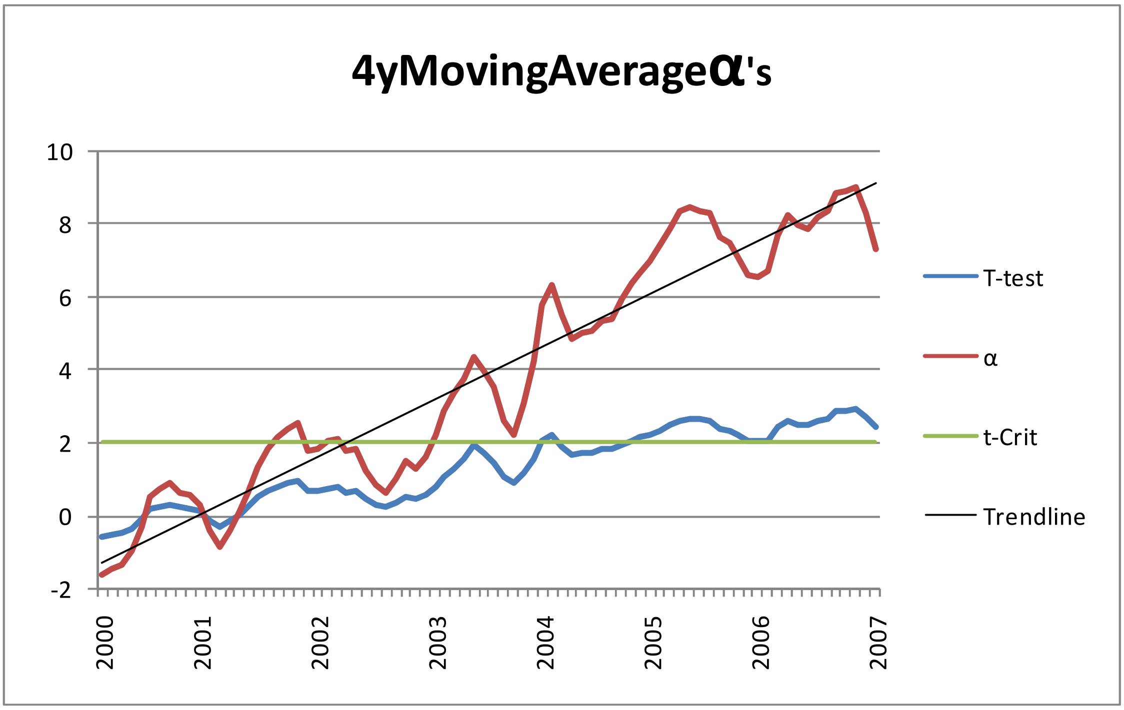


7.2.7 Trends and investor types

From previous studies by Grinblatt and Keloharju (2000) we know that the degree of investor sophistication is strongly correlated to the degree of momentum behavior. In our study of sub periods we have already seen evidence of a trend with increasing momentum profits during the sample period and we wish to check whether trends in the degree of momentum in the Norwegian market is correlated to the relative owner distribution and trade distribution among investor types.

Again we calculate a moving average for the excess return, the alpha, to the momentum strategy. To smooth the returns and get a better graphical illustration of a possible trend we calculate a four year average alpha, moving monthly. This means that the graph starts four years into our sample period (30.06.2000) and ends at the end of our sample period (30.01.2007). We have also calculated a four year moving average t-value, depicted in the graph. We clearly see a positive trend in the excess return to the momentum strategy. The graph shows that an investor following the momentum strategy for a four year period sometime between 2001 and 2007 would earn a significantly (compare a t-critical of 2) positive excess return at the 5% level of between approximately 6% and 9% per six month holding period. Accounting for transactions costs the investor would earn an excess return of between 9% and 15% annually.

Figure 3



Next we want to examine whether there has been a transformation in the types of investors that trades on the OSE during this time period. An increased relative portion of trades in the Norwegian stock market attributable to institutional and foreign more sophisticated investors could be a possible explanation of the trend, in the sense that an increase in the share of momentum traders probably would amplify the actual momentum effect. The relationship between momentum traders and the momentum effect could also be the other way around; the more sophisticated investors could be drawn to markets where momentum exists and in a market with a positive trend in momentum we would accordingly see a positive trend in the share of momentum traders.

The figure depicts the ownership distribution of listed companies on the OSE between various groups of investors from January 2001 to January 2008. The upper graph of the figure shows the percentage owner distribution and the lower graph shows the ownership distribution in billions of NOK (VPS 2008). We see that foreign investors have increased their share of the ownership over the years from 2002, with between 5% and 10%. While their ownership amounted to no more than 200bn NOK in 2001 it is now worth around 800bn NOK. Private company's share of the ownership has remained relatively stable over the whole period while private investors have seen a decrease in percentage ownership. "Central and local government", defined by Grinblatt and Keloharju (2000) as in-between institutional and private investors in the degree of sophistication, has increased their share from 2001 but measured from a high at the beginning of 2003 their share has decreased with approximately 10%.

Figure 4

Owner group	Equities	PCC	Total
Central and local government	34.01 %	1.64 %	33.79 %
Private companies	19.70 %	40.21 %	19.84 %
Mutual funds	3.50 %	4.81 %	3.51 %
Private investors	3.09 %	43.67 %	3.37 %
Foreign investors	39.68 %	9.48 %	39.48 %
Others	0.02 %	0.18 %	0.02 %
Total	100.00 %	100.00 %	100.00 %

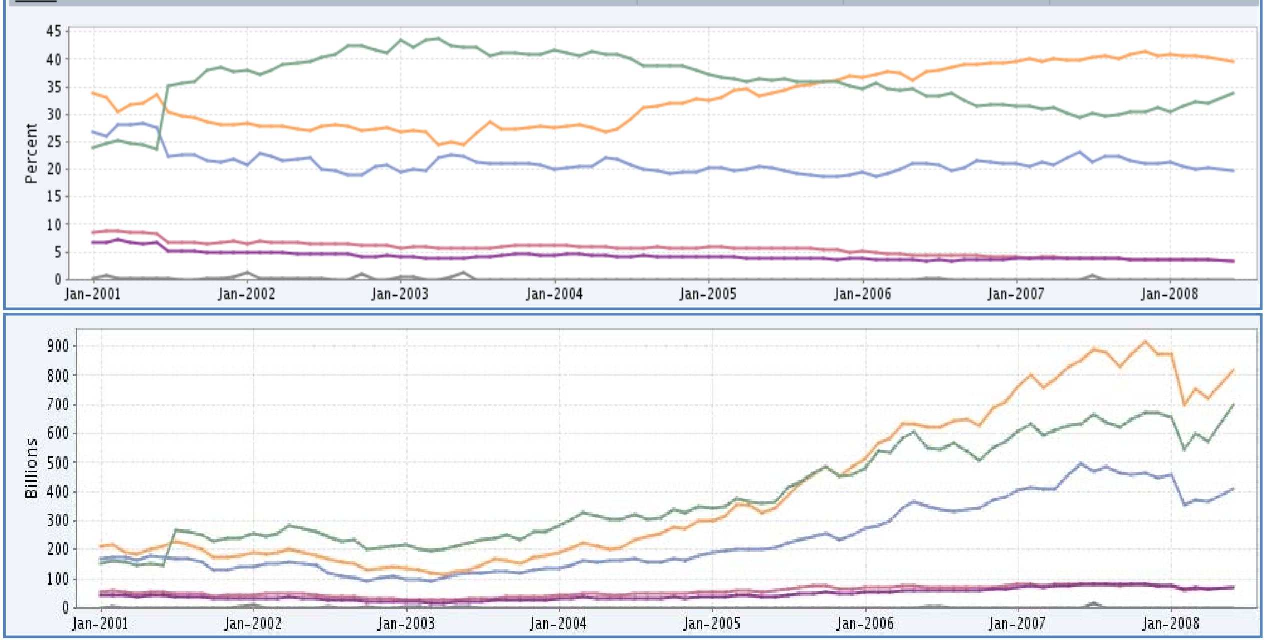
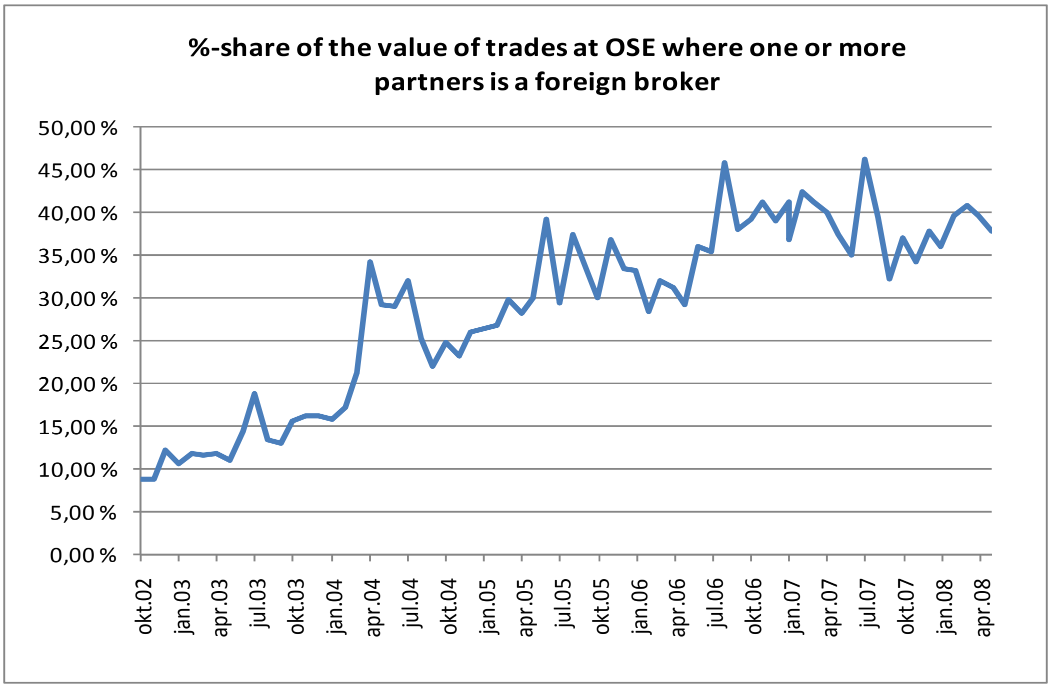


Figure 5 shows statistics from VPS (2008) which illustrates the percentage share of the value of the trades at OSE where at least one partner is a foreign brokerage has increased. This might further strengthen our theory of a change in the trading pattern due to changes in relative magnitude of different investor groups.

Figure 5



We believe that the share of foreign and institutional investors in the Norwegian market contributes to the momentum effect and that the increase in these groups of more sophisticated investors over the years helps explain the trend that we have discovered. However, as discussed above there are other possible explanations behind the cause-effect relation between momentum and investor types. From earlier empirical findings and from behavioral theories we know that momentum is supposed to be higher in small stocks. In this part of the study we operate with a dataset screened for small and illiquid stocks, but still see this positive trend in momentum. This further ads to our theory that a greater presence of momentum traders (i.e. foreign and institutional investors) adds to the momentum effect in the market, since these investor types usually trades stocks that are surrounded by relatively much information and are easier to value, i.e. stocks with relatively large market capitalization. This is contrary to the conservatism theory which predicts underreaction in the market. Instead these findings are more in line with other behavioral theories such as the availability bias which predicts overreaction in the market. If the assumption that an increase in the share of momentum traders actually adds to the momentum effect is correct it could help explain why momentum has not disappeared after becoming known to investors, as has happened with many other anomalies.

We stress that these findings are only circumstantial evidence and further research must be done to infer a conclusion and determine a proper cause-effect relation.

8. Summary and conclusions

This paper documents trends in stock returns in the Norwegian Market during the period between 1996 and 2007. A winner-loser portfolio generated from buying past winners and selling past losers outperforms the market by as much as 3.8% monthly. When accounting for microstructure influences, such as transaction costs and difficulties with short selling, we estimate that a portfolio held for six months subsequent to a six month forming period will earn an excess return on the market marginally higher than 1% per month. The largest contribution comes from the loser portfolio; the winner portfolio has a positive return, but not significantly different from zero.

Our results indicate that the excess returns on the market from momentum trading are not due to systematic risk, nor are they explained by company size or book-to-market ratios. However, loser portfolios tend to load up on small stocks resulting in a winner-loser portfolio that is likely to react positively when large stocks outperform small stocks. Tests of seasonality confirm that the loser portfolio significantly outperforms the winner portfolio in Januaries while the winner portfolio significantly outperforms the loser portfolio during the rest of the year.

Descriptive analyses of the underlying suggest that certain sectors are under or over-represented in the loser and winner portfolios, while others rarely produce returns that put them in either the top or the bottom decile. Variation between sectors is likely to result in part from triggers that are unique to the particular time period being investigated. Further studies over longer time horizons are needed to draw certain conclusions on the features and magnitude of momentum variance across sectors.

By studying business cycles and tendencies in momentum returns during different holding periods we find evidence that contradicts Conrad and Kaul (1998) who argue that excess returns from momentum trading arises from cross-sectional differences in expected returns rather than any predictable time-series variation in stock returns. Our findings show a decline in the excess return over the holding periods and evidence of reversals following bust periods. These results are in line with behavioral theories of overreaction.

Foreign and institutional investors, defined by Grinblatt and Keloharju (2000) as momentum traders, have increased their ownership of securities listed on the OSE between 2001 and 2008 and a larger share of the value of trades can be attributed to foreign brokerages during the same time period. There is also an apparent positive trend in momentum profits during our sample period. This gives us reason to believe that momentum traders add to the momentum effect, which if true could explain why the momentum effect has not disappeared after being recognized by investors. The positive trend in momentum returns and its noticeable parallel to the presence of different types of investors and their trade patterns further strengthens overreaction as a plausible explanation of the momentum effect. However, the cause-effect relationship of investor types to momentum needs to be explored in greater detail to solidify conclusions; it remains a topic for future research.

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